CHARACTERISTICS OF SUCCESSFUL COMMERCIALISATION FROM UNIVERSITY-INDUSTRY RESEARCH COLLABORATION IN ONTARIO, CANADA

by

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DECLARATION

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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ABSTRACT

Canadian firms invest considerably less in research and development as a proportion of GDP than in many other OECD countries. As a result of low private sector research intensity, universities represent a comparatively large proportion of Canadian research. In order to improve university technology transfer and the absorptive capacity of its industries, Canada offers among the highest rates of government support for university-industry research collaboration (UIRC) in the world. The government granting agencies that administer these subsidies seek to identify and fund the UIRC projects that have the greatest likelihood of commercialisation. There is considerable debate among practitioners about what UIRC characteristics are associated with commercial outcomes. Although the mechanisms of effective research collaboration and university technology transfer have been well studied, the academic literature on this specific problem is surprisingly sparse considering its growing importance to policy makers.

This study examined the relationship between the characteristics of various stakeholders in UIRCs, namely academic researchers, universities, firms and governments, and commercial outcomes from UIRC. Specifically, three hypotheses were developed and tested based on the unique context of Canadaôs national innovation system and the extant literature. First, Hypothesis 1 built upon the concept explored in previous studies of how economic behaviour is ñembeddedò in social networks to posit that researchers who are less embedded within academia will have a higher likelihood of commercial outcomes from UIRCs. Next, motivated by the growing body of literature that has found government subsidies help to stimulate greater private sector research expenditures, Hypothesis 2 suggests that UIRCs with higher cash and in-kind contributions by firms will have a higher

likelihood of commercial outcomes. Finally, Hypothesis 3 proposes that UIRCs in industry sectors with higher research intensity will have a higher likelihood of commercial outcomes, since prior studies have demonstrated that research intensity improves firm absorptive capacity.

A novel dataset was developed from the historical records of the Ontario Centres of Excellence, a government granting agency in the province of Ontario, and from other public sources. The UIRC project was the unit of observation and the size of the sample was 682 observations. The dependent variables represented whether or not the UIRC project achieved a commercial outcome. Five independent variables were used to test the hypotheses using binomial and multinomial Logit regression, and 19 additional control variables were included in the model.

Hypothesis 1 was tested using a novel categorisation of researchers based on their level of embeddedness in academia, and found that it was significantly associated with commercial outcomes. However, the results suggested that the directionality of the relationship was opposite to what was hypothesised. Additional testing confirmed that, contrary to what was hypothesised, more embedded researchers have a higher likelihood of commercial outcomes. Therefore, the findings may shed further light on mixed results from previous studies by exploring the commercialisation behaviour of certain categories of embedded researchers.

Hypothesis 2 was tested using separate measures of firm cash and in-kind contributions to UIRCs. The results found that in-kind contributions are significantly associated with commercialisation, but that cash contributions are not. In fact, in-kind contributions are positively associated with licensing outcomes in particular. This study is among the first to link firm contributions to UIRCs with their commercial outcomes at a project level.

Preliminary testing indicated support for Hypothesis 3 by finding a significant and positive association between industry sector and commercialisation. Additional testing found further evidence that UIRCs in industry sectors with higher research intensity had a higher likelihood of commercialisation. The findings suggest important industry differences in UIRC commercialisation patterns. However, the absence of data on UIRCs in life sciences, which represent approximately 50 of all university technology transfer activity, is an important limitation on their generalisability.

The study makes four recommendations to policy makers and government granting agencies based on its findings:

1. Develop awareness and education programs that encourage older, more career advanced and high-quality researchers to become involved in UIRC and commercialisation.
2. Design UIRC support programs and selection criteria to encourage in-kind contributions by firms.
3. Concentrate efforts on developing world class research capabilities and commercialisation infrastructure at a small number of large universities.
4. Focus on supporting research collaboration between universities and the most research intensive industries to maximise the likelihood of commercialisation.

ACKNOWELDGEMENTS

The completion of this thesis has been an incredible journey of self-discovery but I certainly did not do it alone. I would like share this achievement and express my sincere gratitude to those who have supported me academically, professionally and personally through this journey.

I would like to thank Dr. Doug Hyatt for his unwavering encouragement and patience through all the fits and starts over the last five years. Through his thoughtful questions and methodological explanations, he has taught me how to think like a researcher. Dr. James Walker provided a fresh perspective on my work that helped to considerably improve the strength of my arguments and the clarity of the final document.

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DEFINITIONS

AUTM:Association of University Technology Managers

BNL: Binomial Logit

BERD: Business Expenditures on Research and Development

DCM: Discrete Choice Modeling

GERD: General Expenditures on Research and Development

GOVERD: Government Expenditures on Research and Development

HERD: Higher Education Expenditures on Research and Development

IIA: Independence of Irrelevant Alternatives

IP: Intellectual Property

MI: Multiple Imputation

MIS: Management Information System

MNL: Multinomial Logit

NRC: National Research Council

OCE: Ontario Centres of Excellence

R&D: Research and Development

RCA: Research Collaboration Agreement

RDC: Statistics Canada Research Development Centres

TTO: University Technology Transfer Office

UIRC: University-Industry Research Collaboration

U.S.: United States

CHAPTER I: INTRODUCTION

This dissertation is submitted in partial completion of the requirements for the degree of Doctor of Business Administration.

Chapter I is an *introduction* to the purpose of the study, an explanation of the research problem, a description of the data used to address it, and a discussion of its relevance to government policy makers and the academic field.

Chapter II is an overview of *Canadian innovation system*, including its socio-economic structure, the role of firms and universities in research activity, and government policies to encourage knowledge and technology flows between universities and the private sector.

Chapter III is a *literature review* that describes the theoretical basis for the study and discusses how commercialisation and the characteristics of UIRC stakeholders have been defined in prior research.

Chapter IV outlines the *research questions* addressed in the study. It describes a conceptual model based on extant literature and Canadian context that motivates the three hypotheses to be tested.

Chapter V outlines the *methodology* of the study, describes the sources of data and the sampling procedures, defines the various measures that were used, and discusses the various analysis techniques that were employed.

Chapter VI describes the data *analysis* in detail, including various techniques applied to address multicollinearity. The section also provides descriptive statistics of the measures used in the statistical models, the estimation results of those models, and an assessment of the modelsô goodness-of-fit.

Chapter VII interprets the *results* of the hypothesis tests and estimates the marginal effects and predicted probabilities associated with each statistically significant variable in the model.

Finally, Chapter VIII provides a *discussion* of the studyøs findings in the context of the research questions. It describes the limitations of the findings, and their contribution to theory and practice. The section concludes with suggestions for future research that might further build upon the studyøs findings.

1.1: Research Problem

National innovation systems involve a unique set of institutions and policies that interact to generate innovation activity (Niosi, 2008). Canadaøs national innovation system is unique in a number of ways that are important to consider for developing effective policies and for comparing Canada to other jurisdictions. Canada has particularly strong economic, political and cultural ties to both the United States and the United Kingdom, with one foot in the traditions of each country. Resource exploitation also plays an important economic role due to Canadaøs abundance of natural resources. The province of Ontario is Canadaøs manufacturing heartland, but is undergoing a considerable structural shift from industrial to knowledge-based industries.

Canadian firms invest considerably less in research and development as a proportion of GDP than in many other OECD countries, which is largely due to differences in the research intensity of certain Canadian industries compared to other countries. In order to improve private sector research intensity, Canada offers among the highest rates of government support for firm research and development in the world.

As a result of low private sector research intensity, universities represent a comparatively large proportion of Canadian research, the second largest proportion relative to GDP among OECD countries. Therefore, university knowledge and technology transfer is particularly important in Canada. However, there is vast disparity in the scale, reputation and commercialisation output of Canadian universities. Provincial and federal governments invest heavily in various mechanisms to support the commercialisation of university technology, and provide the most generous incentives for UIRCs among G7 countries.

The various stakeholders in UIRCs, namely academic researchers, universities, firms and governments, have different motivations for their involvement in these collaborations (Mowery and Sampat, 2004, Bozeman, 2000):

> **Researchers** at universities engage with firms in order to improve the industrial relevance of their research results, and to augment the pool of financial and other resources dedicated to their research agenda. Researchers have interests that are distinct from, and that occasionally conflict with, those of the **universities** that employ them.
>
> **Firms** engage with universities to help reduce the risk associated with research by gaining access to added expertise and by sharing costs. Firms are recipients of

UIRC outcomes and are the vehicle for their commercialisation. However, they may or may not be seeking commercial outcomes from the collaboration. (Mowery and Sampat, 2004).

Governments seek to facilitate interaction between universities and industry as an important mechanism for knowledge and technology transfer. Government granting agencies provide subsidies to incentivise formal UIRC projects.

UIRCs can have a number of outcomes (Bozeman et al., 2013); ñknowledge-focusedò outcomes include publications and skills development, ñproperty-focusedò outcomes include patents, technology licenses or startups. Property-focused outcomes are the subject of interest in this study, particularly licenses and startups. Government subsidy programs can vary considerably based on the UIRC desired outcomes.

The research problem addressed in this study was to better understand the characteristics associated with achieving commercialisation from university-industry research collaborations (UIRCs), and the extent to which these characteristics influence commercialisation.

1.2: Purpose of the Study

The commercialisation mechanisms of particular interest were *Licenses* and *Startups*.[1] A *License* is an agreement by which the licensor authorises the licensee to use a technology under certain agreed terms and conditions. It is, therefore, a contract freely

[1] It is acknowledged that commercialisation can take many forms. However, for the purposes of this study, the use of the term commercialisation is restricted to licenses and startups, exclusively.

entered into between two parties and contains terms and conditions so agreed.[2] In the context of this study, the licensor is the researcher and/or the university (according to their Intellectual Property ownership policy) and the licensee is generally a firm.

A startup company is a new business that is a separate legal entity from the university whose primary purpose is to commercially exploit technology and knowledge produced from academic activities.[3] The university may or may not be a shareholder in the startup. In the former case, the new entity is sometimes referred to as a spinoff company. This study uses the term startup inclusively and makes no distinction between the two.

The study was concerned with whether a license or a startup was created following a UIRC to commercialise its results. It was not concerned with the extent of the commercialisation but only that a commercial outcome occurred through one of these two mechanisms. For example, the study was not concerned with how much royalty revenue a license had generated, or what volume of sales a startup had generated. Hence, this was not an impact study. Rather, the study aimed to provide insights on this important first step in the commercialisation process (Ambos et al., 2008).

A number of researcher, university, and firm characteristics were measured, along with several measures of the structure of the UIRCs in which they were involved. The characteristics used in the study were *a priori*, meaning they were characteristics that could

[2] Definition from World Intellectual Property Organization (WIPO) [online] http://www.wipo.int/sme/en/ip_business/licensing/technology_license.htm (accessed November 18, 2016).

[3] Definition adapted from Pattnaik, P. Nandan, & Pandey, S. C. 2014. University Spinoffs: What, Why, and How?. Technology Innovation Management Review, 4(12): 44-50.[online] http://timreview.ca/article/857 (accessed November 18, 2016).

be known about the UIRC and its stakeholders before the project started. This distinction was important since it included only the type of information that the stakeholders could use to decide whether or not they wanted to collaborate, and that government agencies could use to determine whether or not to provide funding for a UIRC.

The study made use of historical records on UIRCs funded by the Ontario Centres of Excellence (OCE). OCE is a provincial government organisation in Ontario, Canada that provides subsidies for UIRCs that seek to achieve commercial outcomes. Data obtained from OCE historical records were complemented by data assembled from a variety of other public sources. The result is a novel dataset that includes many of the researcher, firm, university and project characteristics suggested in the extant literature. The creation of this unique dataset provided an ideal opportunity to address this important research topic in an understudied field (Santoro and Saparito, 2003).

1.3: Significance to Practice

Governments provide subsidies in support of UIRCs as a mechanism for creating industrially-relevant technology that has high potential for commercialisation. Government granting agencies that administer these subsidies, such as OCE, must effectively evaluate UIRC project funding applications in order to select the projects that have the greatest likelihood of commercialisation. In Canada, there is debate among policy makers and practitioners within government granting agencies about what UIRC project characteristics are associated with commercial outcomes, such as licenses or startups. The studyǿs author is among these practitioners, and has spent over 17 years overseeing UIRCs and developing government programs that provide financial support for UIRCs in the province of Ontario, Canada.[4] Therefore, the practical significance of this study is to help practitioners identify, among dozens of funding proposals received by government granting agencies each year, which UIRC projects should they subsidise in order to improve the likelihood of commercial outcomes.

The tools commonly employed by funding agencies to evaluate UIRC project applications include peer review and assessment software. Anecdotally, practitioners in the field believe that these tools work well. However, the use of predictive modeling based on past project data has the real potential to complement anecdotal evidence and provide an empirical, data-driven approach to help granting agencies select the UIRCs with the greatest chance of commercialisation. Furthermore, it also has the potential to provide a more objective method of program design and of effectively targeting stakeholder groups and types of projects that are more likely to have commercial outcomes.

1.4: Significance to Theory

As discussed above in Section 1.1, commercialisation is only one of many potential outputs from UIRCs, and UIRCs remain understudied in the academic literature as a mechanism for commercialisation (Santoro and Saparito, 2003). The academic literature on the research problem is surprisingly sparse considering its growing importance to policy makers. The mechanisms and behaviour driving UIRC interaction is well understood in the literature. However, studies on UIRC outcomes are mostly focused on knowledge transfer.

[4] Occasionally in the study, the author makes reference to anecdotal evidence based on his experience as a practitioner, and based on conventional wisdom or best practices shared among practitioners.

Similarly, the mechanisms driving university technology transfer performance are also well understood in the literature. However, studies on commercial outcomes, such as licenses and startups, are mostly focused on the universityøs efficiency in commercialising invention disclosures. Therefore, there is a gap in the literature regarding the characteristics of UIRCs that are associated with commercialisation at a project level.

The study aims to make two important contributions to the literature. First, the study aims to bridge the gap between the literature in the field of 1) university research, and UIRC in particular, and in the field of 2) university technology transfer. The study will accomplish this by testing the relevance of prevailing theories from these related fields to the understanding of UIRC as a mechanism for commercialisation. Second, the study aims to put the studyøs results in a Canadian context, and to recommend policy measures that reflect Canadaøs unique system, but that may also be generalisable to other comparable jurisdictions.

Bozemanøs (2013) review of the literature on research collaboration in universities confirms the need for more work focused on the commercial outputs from UIRCs, finding that research outputs are the most common dependent variable found in the UIRC literature. Bozeman offers encouragement by saying: ñwe look forward to future articles that examine outputs from different perspectives.ò

CHAPTER II: THE CANADIAN INNOVATION SYSTEM

As described in the previous chapter, the goal of this study is to shed light on the factors that lead to the successful commercialisation of university-industry research collaboration (UIRC). A better understanding of these factors would help government agencies that support UIRCs make better decisions that lead to more of the commercial results they seek. Formal collaboration represents only a small part of knowledge flows between universities and firms and UIRCs represent only one formal mechanism for these collaboration. Therefore, the primary goal of this chapter is to put UIRC in the broader context of the role that universities and firms play in creating innovation, and the role that government policies play in encouraging linkages between the two, both in Canada and in other comparative jurisdictions. Another important goal of this chapter is to position this study within the economic, social, institutional, and policy context of the Canadian province of Ontario. The chapter also compares Ontario and Canada to other jurisdictions, to explore the extent to which this studyȏs findings and policy recommendations may be generalisable outside of Ontario.

Typically, the production, diffusion, adoption and mastery of technology are undertaken by firms. This involves not only the development of new products and services of economic significance, but also the processes required for firms to generate new knowledge and to learn (Narula, 2003). Hence, a complex system of policies are required to create linkages between firms and other institutions, to facilitate their interaction, and to promote innovation (Niosi, 2008). These are generally referred to as national innovation systems. A national innovation systems framework is employed in this chapter to describe the Canadian system and compare it to others.

The foundation of national innovation system theory is based on Freemanôs (1987) study of innovation in Japan. The concept was further expanded upon by Lundvall (1992) and Nelson (1993). An alternative stream of research has also been developed to explore sub-national and regional innovation systems, and the interplay of their related institutions and policies within the national system (Braczyk et al., 1998, De la Mothe and Paquet, 2012, Ács, 2000, Cooke, 2001). Nieminen and Kaukonen (2001) defined both national innovation systems and regional innovation systems as ñthe system of organisations and actors whose interaction shapes the innovativeness of the national economy and society.ò

The use of a national innovation system framework represents a ñsystemic approachò to understanding how and why innovation happens, in contrast to a simple ñlinear model of innovationò that assumes that an increase in research and development will directly and proportionally increase the number of new innovations and technologies produced. ñIn realityé ideas for innovation can come from many sources and at any stage of research, development, marketing and diffusion. Innovation can take many forms, including adaptations of products and incremental improvements to processes. Innovation is thus the result of a complex interaction between various actors and institutionsò[5] (OECD, 1997).

Narula (2003) argued that ñfew countries have truly ónationalô systemsò do to the cross-fertilisation of technologies, and Canada is no exception. Therefore, Canadaôs innovation system is compared to that of other countries, including the United States (U.S.) and the United Kingdom (U.K.) in particular. Also, given the focus of this study on UIRCs

[5] See OECD (1997) for more information on national innovation systems, including complementary definitions (p.10) and guidance on the application of the framework.

in Ontario, a discussion of the provincial innovation system is also included in specific cases where the regional system differs significantly from the broader Canadian system.

Given this studyö focus on UIRCs, the discussion is weighted towards describing the institutions, policies and transfer channels related to this form of university-industry linkage in particular. Although both formal and informal channels of collaboration are addressed, the discussion gives particular attention to formal UIRC as the technology transfer mechanism of particular interest to this study.

The dataset used in this study includes university-industry research collaboration projects initiated between 2000 and 2009. Therefore, the discussion focuses on the state of Canadaö national innovation system during the time horizon leading up to and including this period. This helps to more clearly explicate the economic, social, institutional and policy context for the findings and policy recommendations in the study.

2.1: Introduction

Freeman (1987) emphasised the role of political and social institutions in national innovation systems, which he defined as 1) the general structure of the industry, 2) the role of the education and training system, 3) the role of firm-level research and development, and 4) the role of government policy (Wolfe and Gertler, 1998). Following Freeman (1987) and Wolfe and Gertler (1998), this chapter uses a similar framework in its discussion of the Canadian national innovation system.

Section 2.2 describes the socio-economic structure of Canada and of the province of Ontario specifically, including the composition of its population and economy, its skill and employment levels, its key industries, and its ongoing evolution from a resource and industrial economy to an increasingly knowledge-based one.

Section 2.3 discusses firm-level innovation, including the historically low research and development intensity of Canada's firms, and the high degree of foreign ownership of Canadian firms and how that impacts firm size.

Section 2.4 discusses the unique structure of the Canadian university system, and the important role of universities in conducting research and development within Canada's national innovation system.

Section 2.5 describes the government innovation support policies that exist at both the national and provincial level, including direct funding programs to encourage firm-level research and development and Canada's favourable regime of scientific research and experimental development tax credits. Policies and programs that support university-industry research collaboration are examined specifically.

Section 2.6 discusses the interactions between the institutions of Canada's innovation system, including how Canadian firms source innovation, the role of university-industry research collaboration, and a comparison of Canada's university technology transfer performance compared to that of other countries.

Finally, Section 2.7 summarises the chapter and discusses the implications of Canada's unique national innovation system for this study.

2.2: Socio-Economic Industry Structure

Canada is an independent nation located in the northern part of the North American continent. It is a parliamentary democracy composed of a confederation of ten provinces and three territories that extend from the Pacific Ocean in the west, the Atlantic Ocean in the east, and the Arctic Ocean in the north. It is a geographically large country (9.98 million square kilometres), the second largest by land mass in the world behind Russia.

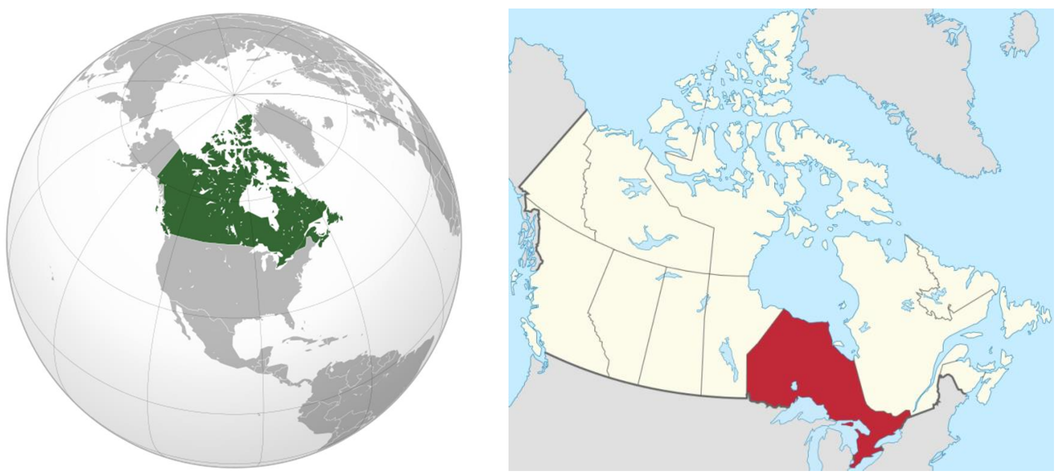

Fig. 2.1: Geographic Location of Canada and Ontario
Source: Wikimedia Commons

Located in east-central Canada, Ontario is Canada's second largest province and is considered the countryôs industrial heartland. It has a land mass of 1.08 million square kilometres, which is an area larger than France and Spain combined (Government of Ontario, 2017). Ontario shares a border with the province of Quebec to the east, the province of Manitoba to the west, Hudson Bay and James Bay to the north. Nearly all of Ontarioôs southern border with the United States runs along inland waterways, including the St. Lawrence River and the Great Lakes (Government of Ontario, 2017).

Canada shares a political border with the United States, which constitutes the longest binational land border in the world. According to the Canadian Broadcasting Corporation (2009), 90 percent of the Canadian population lives within 160 kilometres of the border with the United States. Canadaôs proximity to the United States is an important characteristic of its cultural and economic makeup. Since World War II, Canada has enjoyed a trade surplus with the United States, with Canadian exports of natural resources offsetting imports of finished products and technology (Crane, 2015). In 2009, Canada exported CDN$306.6 billion in goods and services to the U.S., while Canadian imports from the U.S. were CDN$286.2 billion. Trade between Canada and the United States is the largest bilateral trading relationship in the world, totaling CDN$592.8 billion in 2009 (CBC News, 2009). Canada's exports to the United States were CDN$306.6 billion in 2009, equivalent to about 20 percent of Canadaôs Gross Domestic Product (GDP). Canada is also the largest export market for the United States, representing 61.7 percent of Canadaôs imports in 2009 (Government of Canada, 2010). In 2011, over CDN$1.4 billion in trade was conducted across the Canada-U.S. border on a daily basis. Trade specifically between Ontario and the U.S. accounted for approximately CDN$716 million of that amount (Government of Ontario, 2017).

Canada is a former colony of France, and later became a colony of the United Kingdom. In 1867, the four provinces of Ontario, Quebec, New Brunswick and Nova Scotia became a semi-independent federal Dominion of Canada through the British North America Act. In a further step toward independence from the United Kingdom, the Statue of Westminster of 1931 afforded Canada its independence, with the exception of the power to amend Canadaôs constitution, which was retained by the British Parliament. Through the Constitution Act of 1982, Canada repatriated the right to amend its constitution and became a fully sovereign federal parliamentary democracy, while retaining its character as a constitutional monarchy with Queen Elizabeth II as the head of state.

As a result of the unique political, geographic and economic relationship that Canada shares with both the United States and the United Kingdom, Canada is often described as having one foot in each of the cultures of those countries. Hence, despite obvious differences in scale, both the United States and the United Kingdom serve as useful comparators in this discussion of Canadaŏs national innovation system.

2.2.1: Population and Economy

Canadaŏs population and geography has a significant impact on its economy, including transportation and communication costs. It also impacts the structure of its key institutions, as well as the channels of knowledge transfer between universities and firms (Niosi, 2008). Given its large geography, Canada had a relatively low population of 33.5 million inhabitants in 2011. The country is sparsely populated, with 82 percent of inhabitants living in urban areas (Statistics Canada, 2014). With a population of more than 12.9 million in 2011, Ontario was home to approximately 2 in 5 Canadians (Statistics Canada, 2014, Government of Ontario, 2017).

Canadaŏs domestic market is composed of over 27 metropolitan areas that cover a very large geographic territory. More than 85 percent of Ontarians live in urban areas, most commonly in cities bordering the Great Lakes. The largest urban concentration in Ontario is called the "Golden Horseshoe" along the western shore of Lake Ontario, between the cities of Niagara Falls and Oshawa. With over 9 million inhabitants in 2016, the Golden

Horseshoe is ñone of the fastest growing regions in North Americaò (Government of Ontario, 2017).

Canada is one of the wealthiest countries in the world, with a Gross Domestic Product (GDP) of USD$1.28 trillion in 2009. However, Canadaôs population and domestic market is relatively small in comparison to other major industrialised counties such as the United States and the United Kingdom, with GDPs of USD$14.0 trillion and USD$2.25 trillion in 2009, respectively (OECD, 2011). Over the period from 2000 to 2009, Canadaôs GDP per capital fell between that of the United States and the United Kingdom, which performed better on this measure than the European Union average. Therefore, notwithstanding the relative difference in the size of these economies, Canadaôs economic performance is comparable.

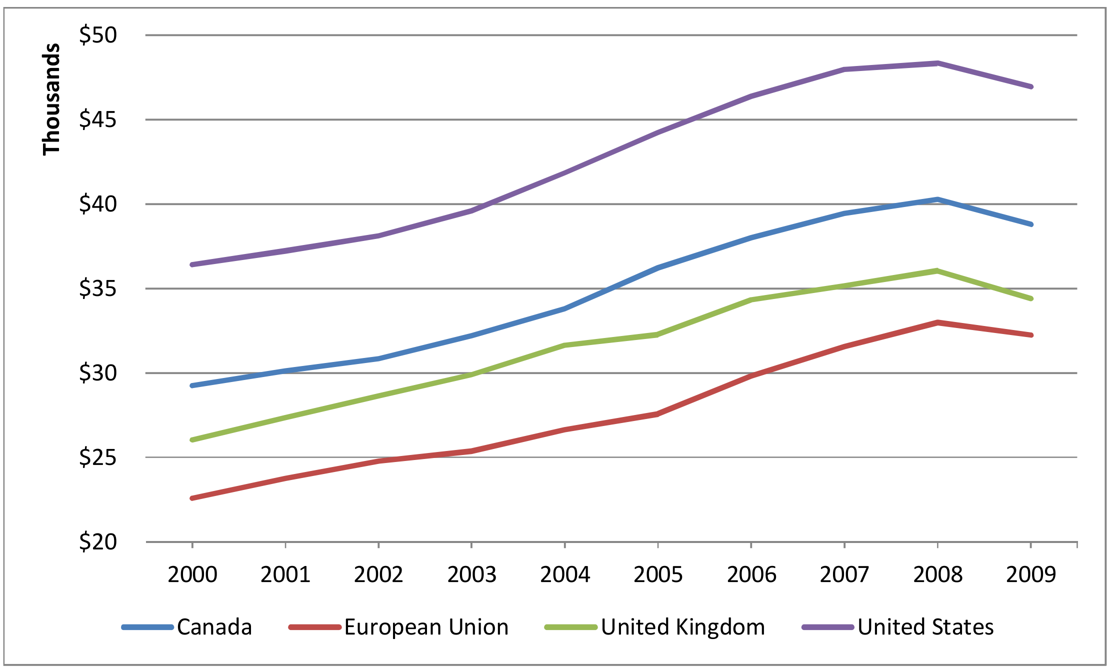

Fig. 2.2: Total GDP in US Dollars per Capita from 2000 – 2009
Source: OECD (2011), National Accounts at a Glance 2010

As in other developed countries, the Canadian economy is dominated by the services sector. Within goods producing industries, resource exploitation plays an important role in the nationâs economy due to the abundance of natural resources, including forestry and mining industries, and oil and gas industries which are primarily focused in western Canada.

Table 2.1: Canadian GDP and Manufacturing Sales by Province in 2012

Province	GDP	Manufacturing Sales
Canada	**$ 1,822,808**	**$ 585,336**
Ontario	**$ 680,084**	**$ 268,119**
Newfoundland and Labrador	$ 32,032	$ 7,161
Prince Edward Island	$ 5,573	$ 1,287
Nova Scotia	$ 37,835	$ 10,460
New Brunswick	$ 31,723	$ 19,527
Quebec	$ 354,040	$ 138,302
Manitoba	$ 59,781	$ 16,333
Saskatchewan	$ 77,957	$ 14,270
Alberta	$ 312,485	$ 71,324
British Columbia	$ 221,414	$ 38,491

Source: Statistics Canada, CANSIM tables 384-0038 and 304-0015

As Canada's most populous province and the manufacturing heartland of the country, Ontario contributed 37.3 percent of Canada's GDP and 45.8 percent of the nationâs manufacturing sales in 2012.

2.2.2: Skills and Workforce

Canadaâs workforce has one of the highest rates of tertiary education in the industrialised world, with rates that are significantly higher than those of key comparators.

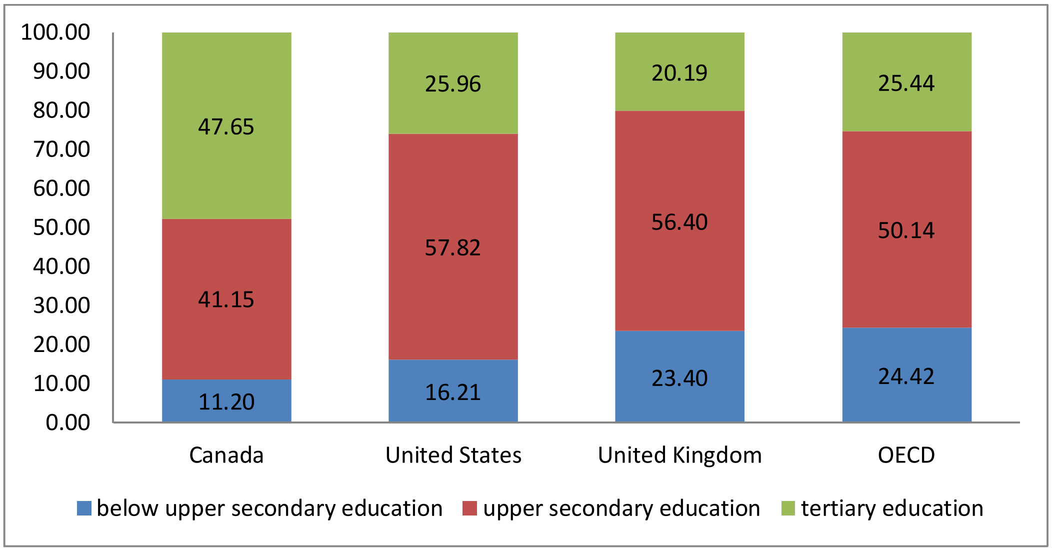

Fig. 2.3: Labour Force by Education Attainment in 2006
Source: OECD Regions at a Glance 2009

The OECD (2009a) found that 47.65 percent of Canadaôs work force has obtained tertiary education, compared to 20.19 percent in the United Kingdom and 25.96 percent in the United States.[6] However, a report by the Expert Panel on Commercialization (2006) found that the story differs significantly at graduate levels of education. The report found a significant gap between Canada and the United States at the PhD level. In 2001, Canada had 429 persons with PhDs per one hundred thousand people, compared with 755 in the United States (Expert Panel on Commercialization, 2006). The report also found that Canadian firms employ fewer PhDs than U.S. firms in nearly all industries.

The skills of a countryôs workforce, especially those in Science, Technology, Engineering and Mathematics (STEM) disciplines, are important components of its

[6] Below upper secondary education includes pre-primary, primary and lower secondary education (ISCED levels 0-2), upper secondary education comprises the ISCED levels 3-4, and tertiary education the ISCED levels 5-6.

national innovation system. Skills and training are the prerequisites for knowledge transfer between individuals, and at a higher level, between institutions such as universities and firms. In this regard, Canadaôs performance is comparable to that of other advanced industrialised nations (Niosi, 2008).

Using data from the National Science Foundation from between 2001 and 2004, Niosi (2008) found that Canada had a relatively high ratio of university graduates in natural sciences and engineering, with bachelorôs degrees in science or engineering awarded at a rate of 7.1 per one hundred 24-year-olds. This was more than in the United States and was the sixth-highest rate among major industrialised nations. More recent data from the OECD (2009b) confirms Niosiôs (2008) findings.

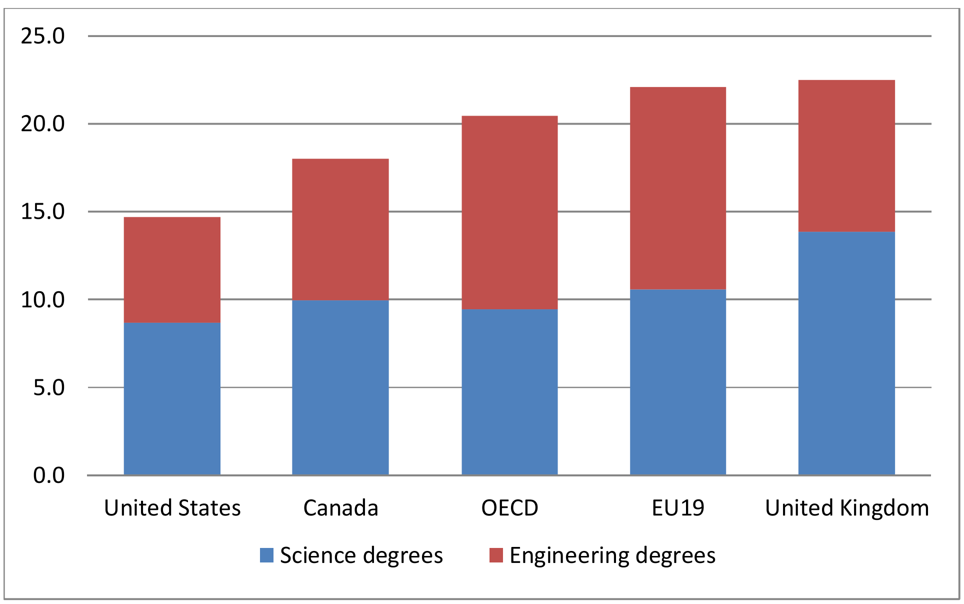

Fig. 2.4: Undergraduate Science and Engineering Degrees as % of New Degrees in 2006
Source: OECD Science, Technology and Industry Scoreboard 2009

The OECDôs (2009b) more recent data showed that Canada remains ahead of the United States in the percentage of undergraduate science and engineering degrees awarded as a percentage of new degrees in 2006, and is ahead of the OECD average for the number of science degrees. Still, Canada lags slightly behind the OECD average, the European Union average and the United Kingdom average in the percentage of science and engineering degrees.

Niosi also found that Canada compares well to other industrialised countries with regard to scholarly publications per capita, ranking eighth in the world on this measure and ahead of the United States.

Table 2.2: Scholarly Publishing in Science and Engineering in 2003

	Articles Published	
Country	Total	Per Capita (millions)
United States	211,236	728
Canada	24,803	775
United Kingdom	48,288	805

Source: OECD (2006), adapted from Niosi (2008)

These results are notable, as scientific publications are an important knowledge transfer channel within the national innovation system.

2.2.3: Industries

Canadaǿs industrial composition incudes a shifting combination of resources and manufacturing industries that have underpinned the economy since World War II, as well as emerging knowledge-based industries such as the ICT sector.

As discussed previously, Ontario is the manufacturing heartland of the country, and contributed 37.3 percent of Canada's GDP in 2012. Ontario is responsible for a disproportionate part of Canadaôs manufacturing sales (45.8%), further highlighting the importance of the manufacturing sector to the province.

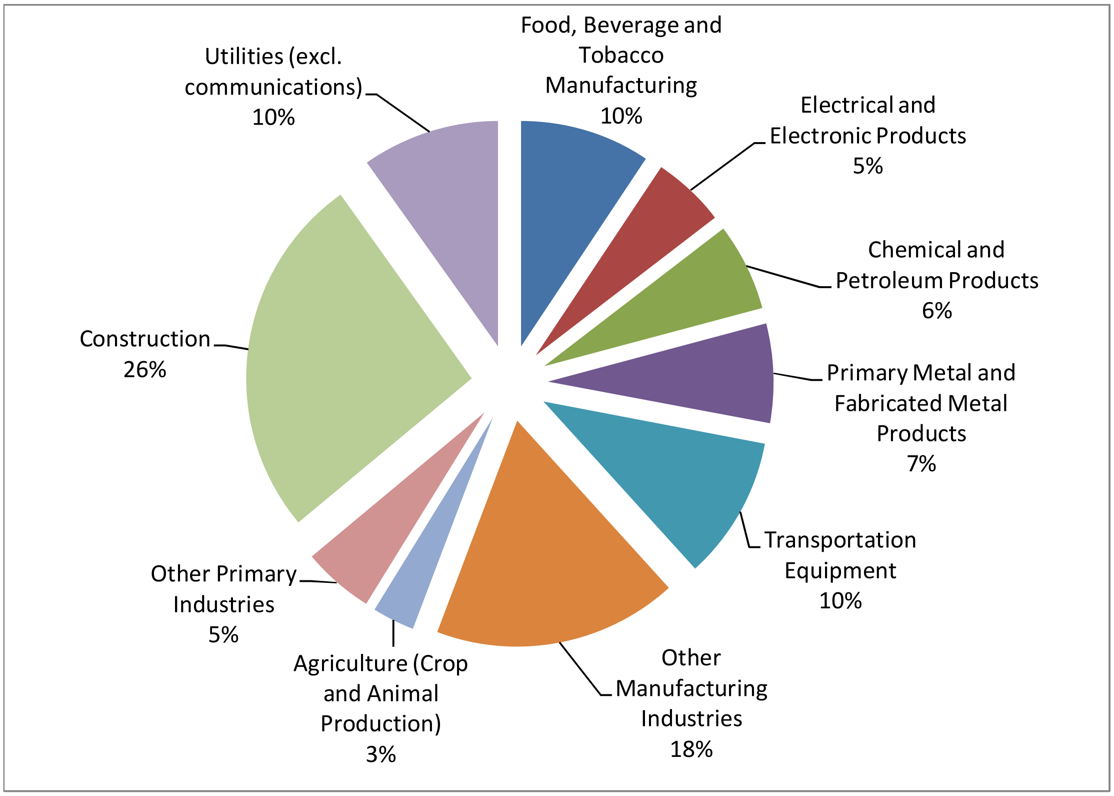

Fig. 2.5: Share of Ontario GDP in Goods Producing Industries in 2009
Source: Government of Ontario, Ministry of Agriculture, Food and Rural Affairs

Among goods producing industries in the province, the manufacturing sector plays an important role in a number of areas including: transportation equipment, metal fabrication, food and beverage, and chemical industries. Automotive production and assembly has been an important driver of economic development and jobs since the signing of the Canadaï US Automotive Products Trade Agreement (known as the Auto Pact) in 1965. Ontario is now the largest sub-national automotive assembly jurisdiction in North America (Government of Ontario, 2017). In 2011, Ontario exported 88 percent of its vehicle production (Statistics Canada, 2013).

The further integration of the Canadian and U.S. economies in the 1980s and 1990s through the Free-Trade Agreement (FTA) and the North American Free Trade Agreement (NAFTA) has had two important implications for Canadian industry, and for the manufacturing sector in particular. First, the free movement of goods, labour and capital across markets has put downward pressure on manufacturing prices. In the period from 1961 to 2005, relative prices in the manufacturing sector fell by 0.9 percent per annum. Production volumes in Canada have remained stable over this period, but lower prices have resulted in an overall decline in the sector (Baldwin and MacDonald, 2009). Declining prices have also made the Canadian manufacturing sector more susceptible to rationalisation and to the downsizing of operations. Second, closer integration of the two economies has led to greater foreign ownership of Canadian firms. By 2012, subsidiaries of U.S. companies accounted for 9.1 percent of Canadaôs corporate assets, and 27.1 percent of manufacturing assets. U.S. owned subsidiaries were responsible for 15.8 percent of all operating revenues, and 26.1 percent of manufacturing revenues in Canada (Crane, 2015). As a result, there are relatively few large companies in Canada, especially in high-technology and knowledge-based sectors.

After a period of relative growth in the 1990s following the FTA and NAFTA agreements, the growth of Canadaôs manufacturing sector stagnated through most of the period between the burst of the ñdot comò bubble at the beginning of the 2000s and the financial crisis of 2008.

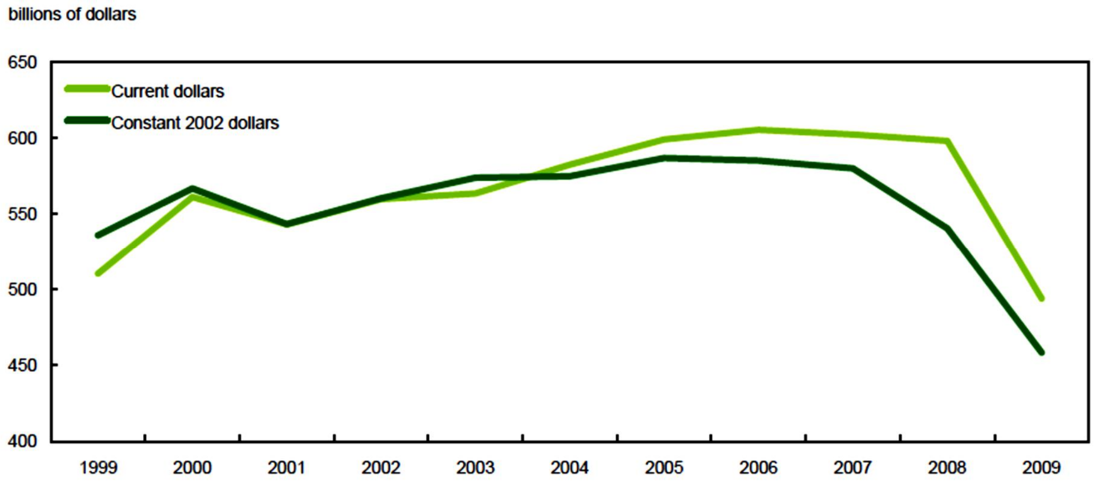

Fig. 2.6: Manufacturing Sales in Canada from 1999-2009
Source: Statistics Canada, Manufacturing industries, CANSIM tables 304-0014 and 377-0008.

Manufacturing growth averaged only 0.4 percent per annum between 2002 and 2007. However, by 2009, manufacturing sales had fallen sharply, and were 18 percent below their peak in 2006 (Harding and Kowaluk, 2010).

In particular, the transportation equipment industry fared rather poorly during the 2000s. Despite moderate growth in the aerospace sector, the automotive sector was down 55.2 percent in 2009 compared to its peak in 1999 (Harding and Kowaluk, 2010).

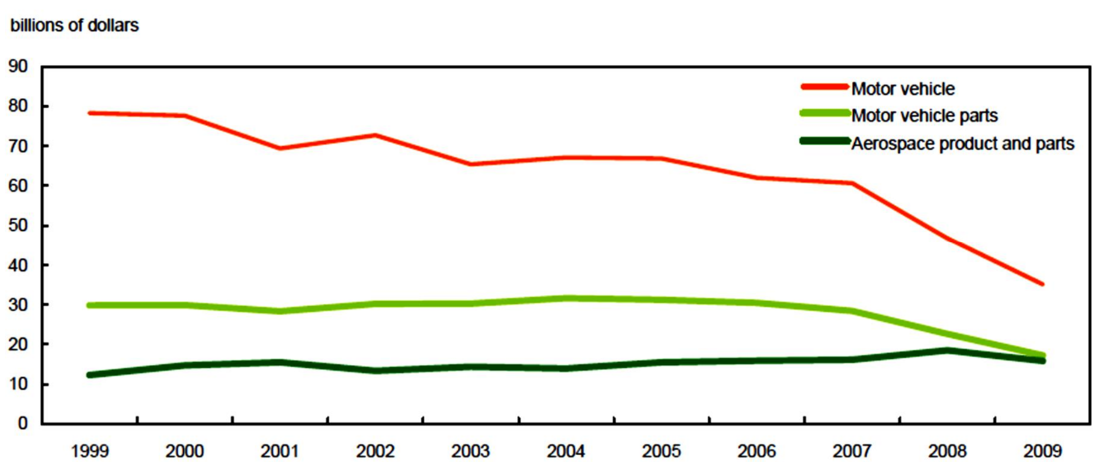

Fig. 2.7: Manufacturing Sales in Canada from 1999-2009
Source: Statistics Canada, Manufacturing industries, CANSIM table 304-0014

To some extent, the decline of Canadian manufacturing over this period was a symptom of the broader restructuring of global production. A similar decline in manufacturing industries was felt in the United States over the same period, where the manufacturing sector was approximately nine times larger than that of the Canadian sector.

Notwithstanding the preceding discussion on the relative importance of the manufacturing sector to Ontarioôs economy, the province is also home to almost 50% of all Canadian employees in high-technology, financial services and other knowledge-intensive industries (Government of Ontario, 2017). Ontario is particularly strong in the Information and Communications Technology (ICT) sector, whose industries ñcomprise the backbone of the global digital economy, and constitute one of the key drivers of productivity growth in the knowledge-based global economyò (Wolfe and Bramwell, 2008). The ICT sector is an important and growing part of Canadaôs economy, representing CDN$59.2 billion and 4.8 percent of Canadaôs GDP in 2008, up from 4.2 percent in 2002 (Wolfe and Bramwell, 2008).

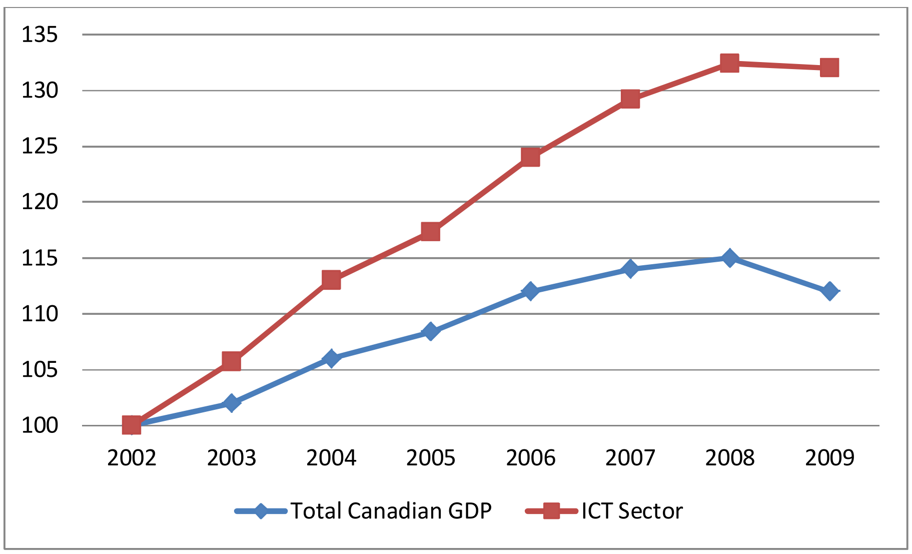

Fig. 2.8: Indexed Growth in GDP for ICT Sector and Canada from 2002-2009
Source: Industry Canada (2011)

The Canadian ICT sector grew by an average of 4.1 percent per year in the period from 2002 to 2009, almost twice the rate of growth of the Canadian economy as a whole (Industry Canada, 2009a).

The Canadian ICT sector is heavily export-driven. In 2008, more than 70 percent of ICT products manufactured in Canada were exported, with the United States accounting for 66 percent of those goods. However, shipments dropped noticeably since 2002, due in large part to the restructuring of the Canadian ICT goods industry as a result of the decline and ultimate bankruptcy of Nortel Networks in 2009. Nortel Networks was a global leader in telecommunications equipment which, at its height in 2000, represented approximately one third of the value of the Toronto Stock Exchange and employed 94,500 people around the world (Hasselback and Tedesco, 2014). Notwithstanding the small size of Canadaös ICT sector relative to other countries such as the United States, Nortelös global market presence helped to make Canada a global player within the industry, and helped to attract talent and capital that have had spillover benefits to other Canadian companies in emerging ICT clusters in Ottawa, Waterloo and Toronto (Wolfe, 2002).

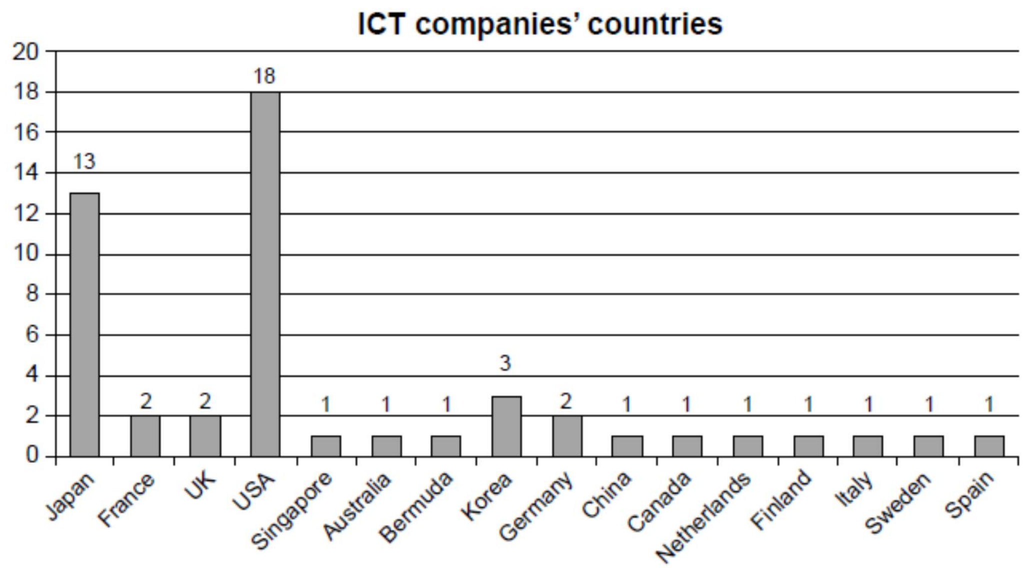

Fig. 2.9: Country of Origin of 50 Largest ICT Firms in 2003
Source: OECD (2004), as presented in Halkos and Tzeremes (2007)

As discussed above, the Canadian manufacturing sector has undergone considerable change since the postwar heyday of the Auto Pact. Nowhere have those changes been felt more drastically than in Ontario, Canadaòs industrial heartland. Global forces have reorganised production capacity around the world and have shifted the structure of the Ontario manufacturing industry to sectors that are more technologically intensive and value added (Wolfe and Gertler, 2001). Over the same period, the ICT sector has grown to become both an economic force and a symbol of Canadian ingenuity that holds great promise for the countryòs future.

2.2.4: An Economy in Transition

The Information and Communications Technology (ICT) sector has grown to rival the automotive sector as an important economic engine and source of jobs in Canada and in the province of Ontario in particular. Over the last decade of the 20th century, the ICT sector was the only manufacturing sector whose growth rate was comparable to that of the automotive sector. ICT actually represented a larger share than the automotive sector of increase in total manufacturing GDP (Wolfe and Gertler, 2001).

As described in the analysis above, the growth rate of the ICT sector outstripped that of the Canadian economy in the 2000s. The ICT sectorâs share of Canadaâs GDP grew by an impressive 34 per cent between 2002 and 2008 (Wolfe and Bramwell, 2008). In contrast, the manufacturing sector was stagnant for much of the 2000s in the face of increasing global competition and declining prices. Transportation industries were particularly hard hit in the later part of the decade, and their relative share of the manufacturing sector fell to 15.4 percent in 2009, down ten percentage points since 1999 (Harding and Kowaluk, 2010).

Although both industries are of considerable importance to the Canadian economy, they are clearly on different trajectories. Many of the reasons for these differences are exogenous, and parallel shifts have also occurred within these industries in other industrialised countries, such as the United States. However, as discussed in the next section on the role of firm research and development with Canadaâs national innovation system, certain factors endogenous to Canada may be compounding these exogenous forces in unique ways.

2.3: Firm Research and Development

As the primary performer of research and development in most industrialised countries, firm innovative performance is a key driver within the national innovation system, and Canada is no exception. This section explores Canadaâs research and development performance compared to other industrialised countries, compares firm expenditures on research and development in different industries, and discusses the reasons for Canadaǿs relatively low research intensity.

2.3.1: Canada's Research and Development Performance

Traditionally, Canada has invested significantly less in research and development than many other OECD countries. In 2006, Canada was ranked fifth among G7 countries on gross domestic expenditure on research and development (GERD) relative to GDP (Expert Panel on Commercialization, 2006).

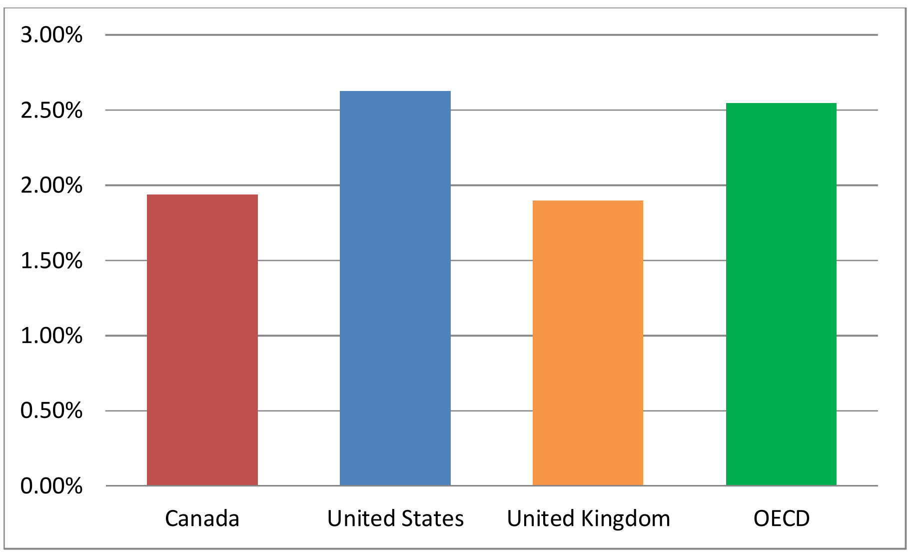

Fig. 2.10: GERD as Percentage of GDP in selected countries in 2003
Source: OECD (2005), adapted from Expert Panel on Commercialization (2006)

At 1.9 percent in 2003, Canadaǿs GERD-to-GDP ratio is also below the OECD average of 2.2 percent, and falls well behind those of smaller countries such as Sweden (4.0 percent) and Finland (3.5 percent).

Canadaøs weak aggregate research and development performance relative to comparable countries is largely attributable to firm activity (Iorwerth, 2005).

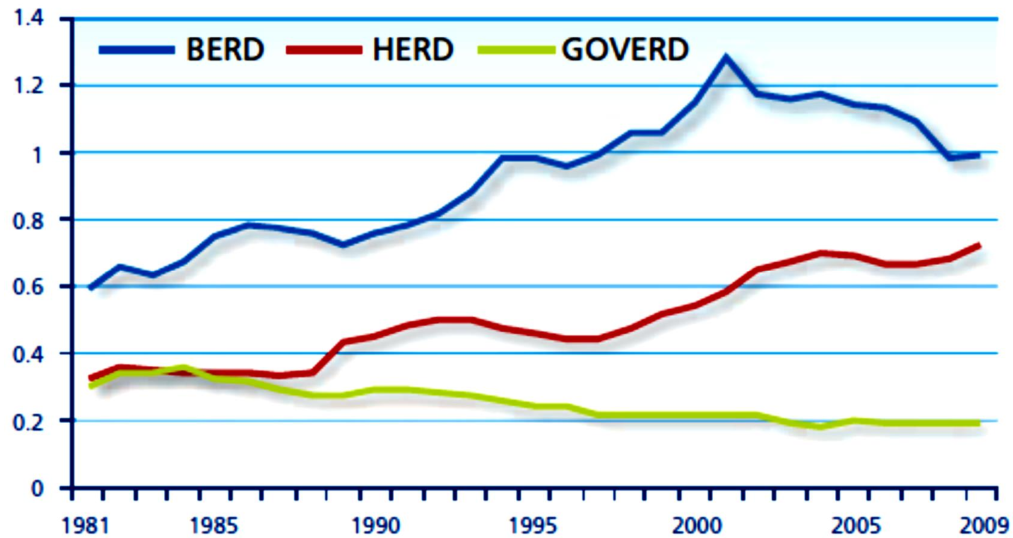

Fig. 2.11: Research Expenditures in Canada as a % of GDP by Performing Sector in 2010
Source: OECD (2010), as presented in Jenkins Report (2011)

As evidenced in Figure 2.11, the relative importance of business expenditures on research and development (BERD) to Canadaøs research intensity has decreased significantly from 1.3 percent of GDP in 2001 to just under one percent of GDP in 2009. Over the same period, the relative role of higher education research and development (HERD) increased by 25 percent (Jenkins Report, 2011). The relative importance of research and development conducted by government laboratories (GOVERD) has been declining since 1983.

2.3.2: Firm Expenditures on Research and Development

Firms are generally considered the main beneficiaries of university research and development. Firms with higher levels of expenditure on research and development have a greater absorptive capacity, defined as the firmøs ability to value, assimilate, and apply new knowledge (Cohen and Levinthal, 1990). Higher absorptive capacity of firms within a national innovation system should, in turn, lead to higher levels of university-industry research collaboration and stronger technology transfer channels between universities and industry. Therefore, understanding the research and development performance of Canadian firms is critical to the interpretation of this studyós results.

As described above, the research intensity of Canadian firms is lower than the OECD average. In particular, Fig. 2.11 suggests that the research intensity of firms in Canada is lower than it is in the United States and the OECD average, but slightly above that of U.K. firms.

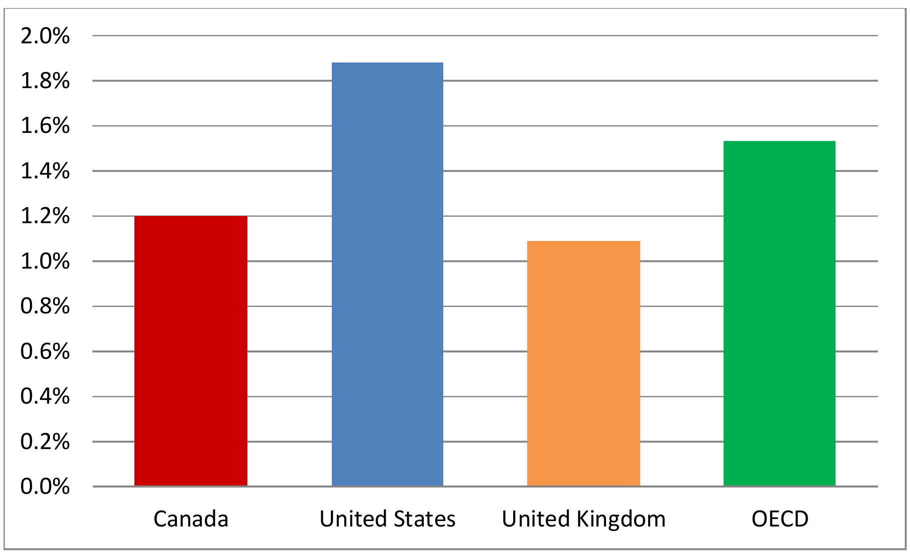

Fig. 2.12: BERD as Percentage of GDP in selected countries in 2004
Source: OECD (2006), adapted from Niosi (2008)

With regard to BERD performance of Ontario firms in particular, Figure 2.12 suggests that Ontario performed better than all other Canadian provinces with the exception of Quebec in 2008. However, BERD intensity of Ontario still lags the OECD average considerably.

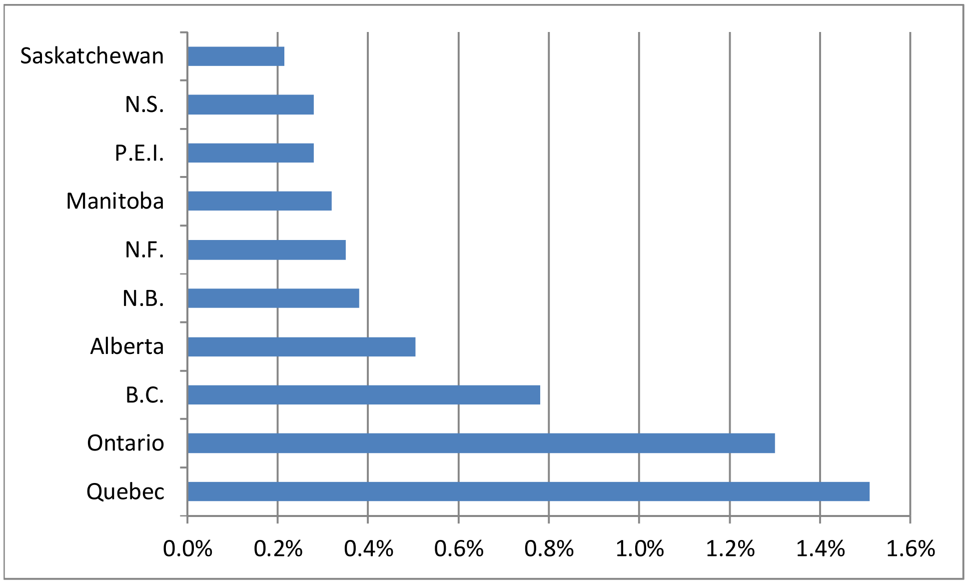

Fig. 2.13: BERD Intensity as a Percentage of Provincial GDP in 2008
Source: Statistics Canada (2010) and OECD (2011), adapted from Jenkins Report (2011)

Certainly, there are inherent issues with the structure of Canadaǿs economy that explain Canadaǿs poor aggregate performance, such as the size of its primary resource industries, which are generally known to have low research intensity (Niosi, 2008). However, there are differences in the research intensity of certain other industries in Canada compared to other countries, such as the United States. The degree of foreign ownership and the relatively small size of Canadian firms are also important factors, which are discussed in more detail in the next section.

2.3.3: Deconstructing Canada's Poor R&D Performance

It would appear that important differences in a few key industries can actually account for a significant portion of Canadaǿs traditionally poor performance on BERD compared to other countries.

Iorwerth (2005) compared the R&D intensity in certain key industries in Canada with those in the United States.

Table 2.3: Research Intensity by Industry in Canada and the United States in 2005

	Canada			United States		
	Share of R&D	**Research Intensity**	**Share of GDP**	**Share of R&D**	**Research Intensity**	**Share of GDP**
Manufacturing:						
Office & Computer Equip.	4.89%	53.63%	0.10%	5.21%	25.80%	0.39%
Radio and Telecom Equip.	28.93%	27.87%	1.10%	20.63%	20.54%	1.95%
Pharmaceuticals	6.49%	27.51%	0.25%	6.82%	20.92%	0.63%
Other Transportation	11.95%	14.48%	0.88%	8.75%	24.25%	0.70%
Electric Machinery	1.14%	3.63%	0.33%	2.34%	10.86%	0.42%
Mechanical and Electrical	2.48%	2.09%	1.26%	3.51%	5.50%	1.24%
Plastic and Chemicals	3.39%	1.63%	2.21%	5.83%	5.33%	2.12%
Basic Metals	1.40%	1.28%	1.15%	0.26%	0.93%	0.54%
Textiles	0.71%	1.06%	0.71%	0.19%	0.64%	0.57%
Fabricated Metal Products	1.20%	1.03%	1.23%	0.94%	1.59%	1.15%
Furniture	0.59%	0.76%	0.82%	0.48%	1.58%	0.59%
Motor Vehicles	2.03%	0.75%	2.86%	10.13%	15.30%	1.28%
Food and beverages	1.17%	0.55%	2.27%	0.85%	0.98%	1.68%
Wood and Paper	1.53%	0.39%	4.13%	1.64%	1.44%	2.21%
Other Mining Products	0.13%	0.29%	0.46%	0.34%	1.49%	0.44%
Total Manufacturing	**68.02%**	**3.65%**	**19.75%**	**67.91%**	**8.27%**	**15.91%**
Services:						
Community/Social Service	0.00%	0.00%	19.77%	0.00%	0.00%	21.17%
Hotels and Restaurants	0.00%	0.00%	2.43%	0.00%	0.00%	0.86%
Transport and Storage	0.21%	0.05%	4.28%	0.26%	0.15%	3.24%
Financial Intermediation	1.97%	0.30%	6.97%	0.87%	0.21%	8.04%
Post and Telecoms	0.92%	0.35%	2.79%	0.87%	0.49%	3.43%
Wholesale and Retail	7.41%	0.69%	11.31%	11.06%	1.25%	17.08%
Real estate	19.28%	1.11%	18.41%	12.15%	1.12%	20.95%
Other				6.41%		
Total Services	**29.79%**	**0.48%**	**65.97%**	**31.62%**	**0.82%**	**74.77%**

Source: OECD (2005), adapted from Iowerth (2005)

The Canadian economy includes a number of large sectors, such as primary resource industries, that exhibit low research intensity not only in Canada, but in most industrialised countries (Nicholson, 2003). However, Table 2.3 shows that, on a comparative basis by industry, Canadian research intensity was considerably lower than that of the United States in 2005. The relative research intensity of the Canadian and U.S. automotive sector is particularly notable; although the sector is over twice the size in Canada as a percentage of GDP, automotive research intensity in Canada is negligible compared to in the U.S. (0.75% and 15.3%, respectively).

Canadian BERD was highly focused in three areas: the ICT sector, pharmaceuticals, and the aerospace industry. It was also highly concentrated, with 100 companies representing over 56 percent of Canadian BERD in 2006 (Niosi, 2008). Research spending in the ICT sector represented 38 percent of total BERD in 2008. The ICT manufacturing sub-sector was the largest spender, with a value of CDN$3.2 billion, or 51 percent of ICT sector research spending and 19 percent of Canadian BERD in 2008 (Industry Canada, 2009a).

Iorwerthǿs (2005) analysis provided important evidence that Canadaǿs lower BERD intensity was primarily due to comparatively lower R&D intensity in key industries, such as the automotive and service sectors, rather than to differences in industry structure. In fact, the analysis shows that the research intensity of Canadian firms in the ICT sector is considerably higher than that of U.S. firms; by a ratio of 2.08:1 in the office and computer equipment sector, and 1.36:1 in the radio, TV and communications equipment sector (Jenkins Report, 2011).

As described earlier, the Canadian economy is characterised by an increasingly high degree of foreign ownership, by the U.S. in particular. As a result, foreign firms are responsible for much of the research performed in Canada, especially in certain technology-based industries such as pharmaceuticals. This may create preferences or economies of scale that explain the concentration of research activities in the United States (Iorwerth, 2005).

Another important factor that may influence research intensity is firm size. Canada has a surprisingly low number of large science and technology-based firms. In 2006, there were only 13 Canadian firms on the Fortune Global 500 list of the worldôs largest firms, of which only three were in science and technology based industries: Bombardier (aerospace), Magna (automotive parts) and Nortel Networks (ICT) (Niosi, 2008). In Canada, many advanced technology startups are created, but most are acquired by U.S. and other foreign multinationals before they achieve significant scale.

Indeed, there appear to be a number of explanations for Canadaôs relatively poor BERD. The Expert Panel on Commercialization (2006) suggested that ñthree quarters of the gap in Canadaôs R&D intensity relative to the U.S. is attributable to lower R&D intensities across industries.ò Specifically, the difference is largely attributable to the wholesale trade, retail trade and automotive industries. Research intensity in the Canadian ICT sector compared favourably with that of the U.S. Although the ICT sector represented a smaller proportion of the Canadian economy than the automotive sector, it is growing at a faster rate. This further underscores the transition in the Canadian economy from traditional manufacturing industries to knowledge-based industries.

2.4: The Role of Universities

Universities are critically important institutions within national innovation systems (Niosi, 2008). They create the human capital that allows knowledge and technology to be absorbed and adapted (Lau, 1996). Higher education increases a firmôs capacity to absorb technology and put it to efficient use (Lim, 1999).

If the absorptive capacity of firms based on their research intensity is the ñdemand sideò of the Canadian innovation system, then it can be said that universities represent the ñsupply sideò (Niosi, 2008). However, the importance of universities in the national innovation system can be considerably different from one country to the next. For example, universities are particularly important sources and diffusers of technology to industry in the European system. In the United States, universities often form the core of technology clusters that emerge in key sectors, around which related firms and other research institutes gather with varying levels of formality and sophistication (OECD, 1997). As discussed below, Canadian universities and firms are involved in a uniquely high level of research collaboration.

2.4.1: Structure of University System in Canada

The Canadian constitution assigns responsibility for education, including higher education (including universities) to the thirteen provincial and territorial governments. Although provincial and territorial governments are responsible for universities, the federal government contributes indirectly to funding the operational costs of universities through a system of transfer payments to the provinces and territories. In 2010, the federal government transferred CDN$ 3.4 billion to the provinces and territories in support of post-secondary education (Currie and Standards, 2011).

In 2010, there were 21 universities in Ontario, including the Royal Military College of Canada in Kingston, which falls under federal jurisdiction given its ties to the armed forces. The government of Ontario has consistently invested in its postï secondary education systems since the 1960s, and its research universities ñcan be thought of as the bedrock of Ontarioôs economic development policyò, and have been responsible for a generally high levels of educational attainment compared to other provinces or many U.S. states (Wolfe and Gertler, 2001).

Using OECD data, Niosi (2008) found that expenditures on post-secondary education in Canada were 2.6 percent of GDP in 2006, compared to 3.1 percent in the United States, 1.3 percent in the United Kingdom, and an average of 1.5 percent across all OECD countries.[7]

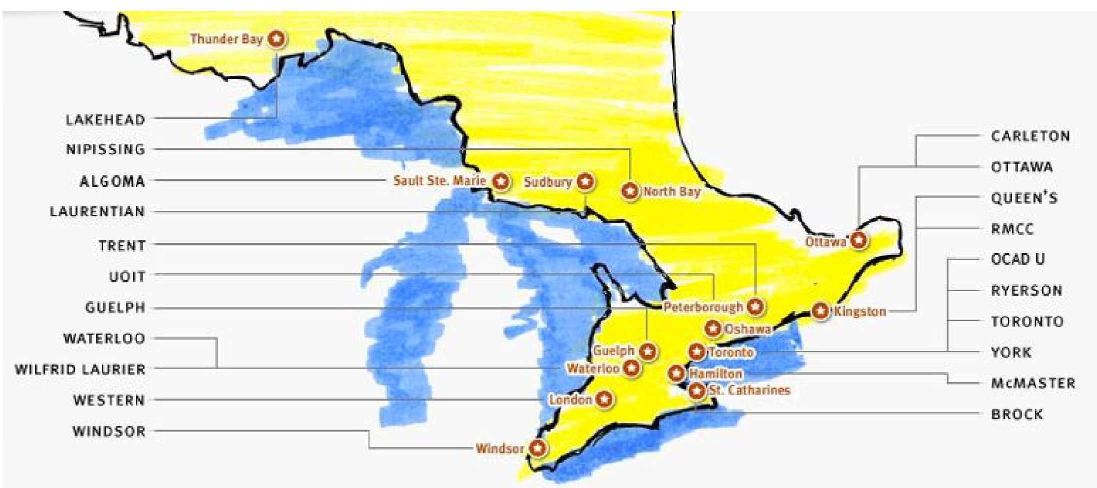

Fig. 2.14: Geographic Location of Universities in Ontario
Source: Joy Werner, Brock University Faculty Association

[7] In cases where 2006 data was not available, Niosi (2008) used the most current data available.

Although some private degree-granting universities exist in Canada, the publicly funded university system represents the vast majority of enrollment and virtually all research activities. Of Ontarioôs 21 public universities, 18 are actively involved in research and development activities.[8] The federal government funds research and related infrastructure at Canadian universities through a complex set of mechanisms, the most important of which are three federal granting councils: the Natural Science and Engineering Research Council (NSERC), the Social Sciences and Humanities Research Council (SSHRC), and the Canadian Institutes of Health Research (CIHR).

2.4.2: Higher Education Expenditures on Research and Development

Much like in Europe, Canada has a relatively important public research sector and a small domestic market (Rasmussen, 2008).

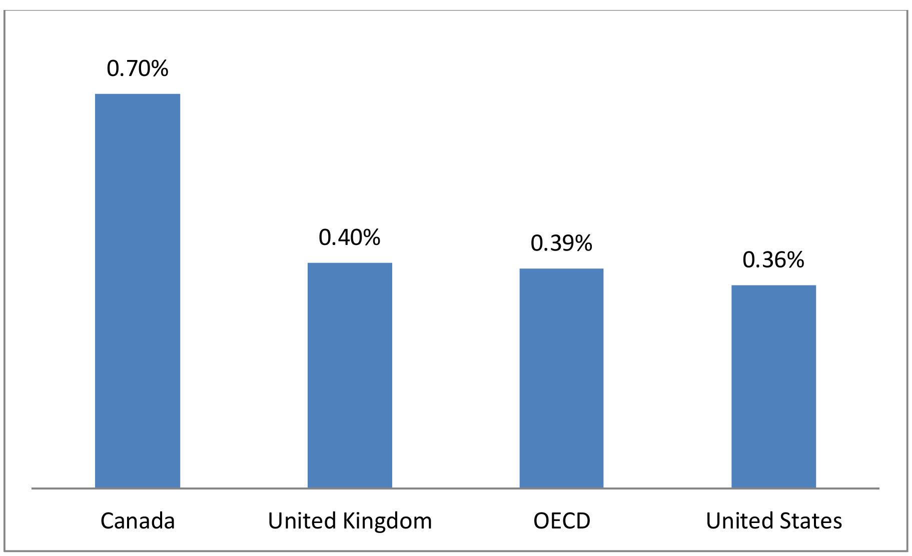

Fig. 2.15: Higher Education Expenditures on Research as % of GDP in 2004
Source: OECD (2006), Adapted from Niosi (2008)

[8] Algoma University, the Royal Military College of Canada, and the Ontario College of Art and Design University were not materially involved in research and development activities in 2010.

In 2004, Canada was second among OECD countries in terms of its expenditure on university research and development as a percentage of its GDP, behind only Sweden and with twice the rate of the United States. University research represented 36.8 percent of general research and development expenditures (GERD) in Canada in 2010, a share that has been increasing steadily since 1997 (Niosi, 2008).

There is a vast disparity in the size and scale of research activities, and by association the reputation, of Ontarioȏs universities.

Table 2.4: Research Capacity and Reputation of Ontario Universities in 2010

University	Sponsored Research	Research Rank	Reputation Rank (Ont)	Reputation Rank (CAN)
Toronto	$ 878,725,000	1	2	4
McMaster	$ 395,364,000	2	3	6
Ottawa	$ 273,278,000	3	9	23
Western	$ 221,236,000	4	5	8
Queen's	$ 197,016,000	5	4	7
Guelph	$ 148,905,000	6	6	11
Waterloo	$ 144,299,000	7	1	1
Carleton	$ 70,456,000	8	11	32
York	$ 69,379,000	9	13	36
Windsor	$ 28,348,000	10	15	42
Ryerson	$ 22,524,000	11	7	17
Laurentian	$ 22,428,000	12	16	43
Lakehead	$ 17,359,000	13	17	44
Brock	$ 15,655,000	14	12	34
Trent	$ 13,641,000	15	14	40
Wilfrid Laurier	$ 9,997,000	16	8	21
UOIT	$ 8,312,000	17	10	30
Nipissing	$ 1,693,000	18	18	47

Sources: Macleanȏs Magazine Reputational Survey of Canadian Universities 2010
Research Infosource ranking of Canadaȏs Top 50 Research Universities 2010

In 2010, the University of Toronto was the largest research university in Ontario by a wide margin, representing 35 percent of all university sponsored research in the province.

Its CDN$878.4 million in sponsored research is more than double that of McMaster University, the next largest university with CDN$395.4 million in sponsored research. With the exception of the University of Toronto, the research capacity of most of Ontarioĝs universities was relatively small when compared globally. The University of Toronto and McMaster University were the only academic institutions in Ontario to rank within the top 100 universities in the world by research in 2010 (Times Higher Education, 2011).

Table 2.5 also compared Ontario universitiesô research ranking with their reputational ranking, and their relative reputation compared to all Canadian universities. It was reasonable to assume that universities with larger research budgets would attract better researchers, who in turn would attract better students. Therefore, it was not a surprise to see a relationship between the research capacity and reputational ranking of Ontario universities. Once again, only the University of Toronto and McMaster University were within the top 100 universities in the 2010 academic ranking of world universities (Shanghai Ranking, 2011). However, there were some exceptions. The University of Ottawa ranked significantly lower on reputation compared to research capacity. The University of Waterloo is a relatively small research institution, but has world class mathematics and engineering research programs. It is also recognised as an important part of the emerging Waterloo ICT cluster, which further bolsters its reputation compared to its size. Ryerson University and Wilfrid Laurier University score well in teaching excellence, which improves their reputational ranking compared to their research capacity.

Not surprisingly, there is also considerable disparity among Canadian universities in commercialisation outputs. In 2004, the top 25 universities in Canada in terms of funded research accounted for 85 percent of all university inventions, over 90 percent of all patents granted to universities, 95 percent of all licensing royalties to universities, and 78 percent of all startups (Niosi, 2008). A number of studies and reports have shown that the commercialisation output of Canadian universities is significantly lower than that of universities in the United States. Although academic publishing rates are similar between both countries after controlling for differences in size, ñwide differences persist among universities in the two countriesô ability to patent, license and create spinoff companiesò (Niosi, 2008). As discussed below, at least some of these differences can be explained by appropriately controlling for the relative size of the different university systems, and for their policy environment.

Obviously, policy differences between countries may in part explain the relative difference in both firm and higher education research and development performance. This subject will be explored in more detail in the next section.

2.5: Government Innovation Support Policies[9]

The Canadian federal government policy framework to support innovation began in the 1970s, in growing recognition of the importance of innovation as a driver of economic growth (Solow, 1956). The Lamontagne Report of 1970 was among the first in Canada to call for the creation of a national innovation policy, which led to the creation of the Ministry of State for Science and Technology in 1971 and a number of programs to support research and development within firms and academia. The Macdonald Commission Report of 1984 set out a number of recommendations for supporting Canadaôs knowledge-based

[9] The introduction to this section on the historical context of Canadian innovation policy was largely adapted from the report from the Expert Panel on Commercialization (2006).

economy within an increasingly global economic context, leading to the formalisation of the Scientific Research and Experimental Development Tax Credit in 1986. In response to a widening productivity gap between Canada and other countries in the 1990s, notably the United States, the Canadian government substantially increased funding for research and development, for tax credit support, and for skills and education, as drivers of economic growth. By the early 2000s, Canada had one of the most generous research tax incentive programs in the world, and over 100 programs to support innovation and commercialisation managed by over 25 various departments and agencies, the largest of which was Industry Canada.

2.5.1: Policies Supporting Firm Research and Development

In an effort to bolster the lagging expenditures on research and development by Canadian firms as described in Section 2.3, the government of Canada provides among the highest rates of direct and indirect support for BERD compared with other industrialised countries. In 2010, approximately 81 percent of all federal government support for research and development was directed to firms (Jenkins Report, 2011).

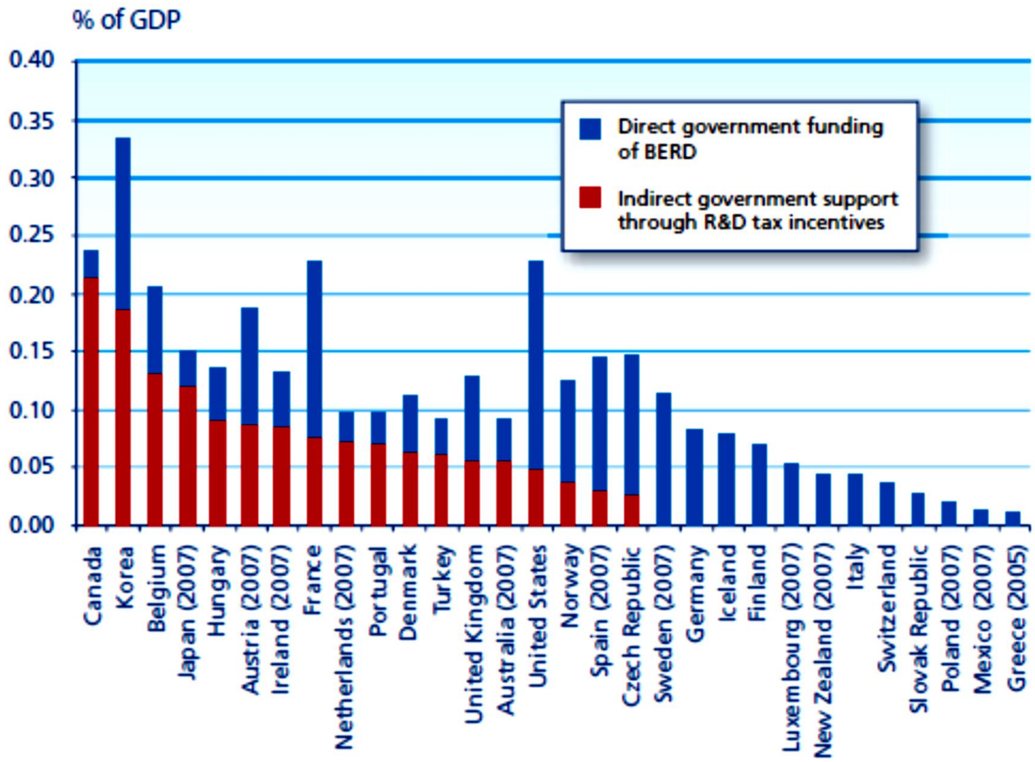

Fig. 2.16: Government Support of BERD as Percentage of GDP in 2010
Source: OECD (2010), as presented in Jenkins Report (2011)

It should be noted that the data in Figure 2.16 does not include additional tax incentive provided by provincial governments. Therefore, the incentives available to Ontario firms are actually greater than shown. In 2010, approximately 86 percent of federal government support for BERD was delivered through the Scientific Research and Experimental Development (SR&ED), the largest federal research and development support program by a significant margin (Jenkins Report, 2010).

Other countries, such as the United States, also offer tax incentives in support of BERD, however Canadaǿs SR&ED tax credits are generally acknowledged as being more advantageous for firms than the U.S. scheme.

Table 2.5: Comparison of Canadian and U.S. R&D Tax Incentive Programs

Canada	United States
• 20% federal tax credit for all SR&ED expenditures (provincial SR&ED tax credits also available in all provinces except P.E.I.).	• 20% federal tax credit for incremental R&E. (State R&E tax credits also available in certain states).
• 35% refundable SR&ED tax credit available to certain Canadian Controlled Private Corps.	• No refundable R&E tax credit
• Qualifying SR&ED expenses include salary and wages, materials, contract payments, leases, overheads, and capital expenditures.	• U.S. definition of R&D is more restrictive than Canadian SR&ED definition.
• No restriction on eligible SR&ED contracts (100% of amount to be claimed).	• Eligible R&E contracts restricted to 65% of contract amount.
• 100% write-off for eligible SR&ED equipment.	• No accelerated write-off for R&E equipment.
• Unused SR&ED tax credits can be carried back 3 taxation years and forward 20 taxation years.	• Unused R&E tax credits can be carried back 1 taxation year and forward 20 taxation years.
• SR&ED tax credit is permanent.	• R&E credit is extended every few years. It has not yet been made permanent.

Source: PriceWaterhouseCoopers Canada, as presented in Currie and Standards (2011)

Among direct expenditures by the federal government in support of research and development in 2010, 37 percent was directed towards firms, 27 percent was directed towards universities, and 21 percent was directed towards federal research institutes, the largest of which is the National Research Council.

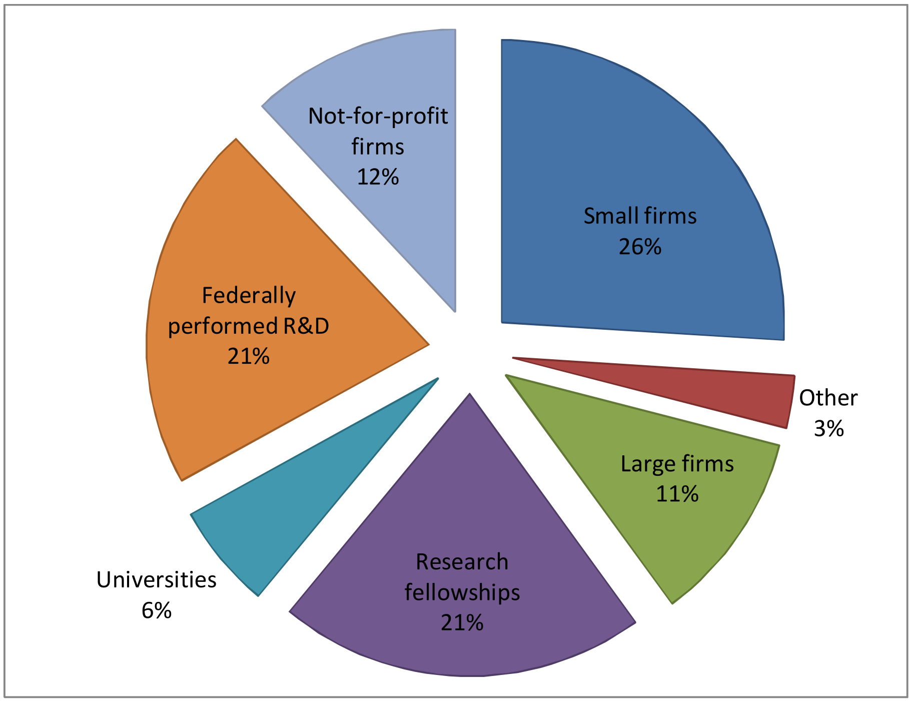

Fig. 2.17: Direct Federal Government Expenditures on R&D in 2010
Source: Jenkins Report (2011)

In 2010, direct funding programs represented approximately 30 percent of federal government support for research and development (70 percent was indirect support through SR&ED tax credit). However, there were 59 direct support programs, the largest and most significant direct BERD support program is the Industrial Research Assistance Program (IRAP), a broad-based program that provides funding coupled with advisory services to support research and development projects by small and medium-sized enterprises (SMEs). Direct federal support for university research is channeled through three agencies: the Natural Science and Engineering Research of Canada (NSERC); the Social Science and Humanities Research Council of Canada (SSHRC); and, the Canadian Institutes of Health Research (CIHR). These agencies use a typical academic peer review process to award competitive research grants.

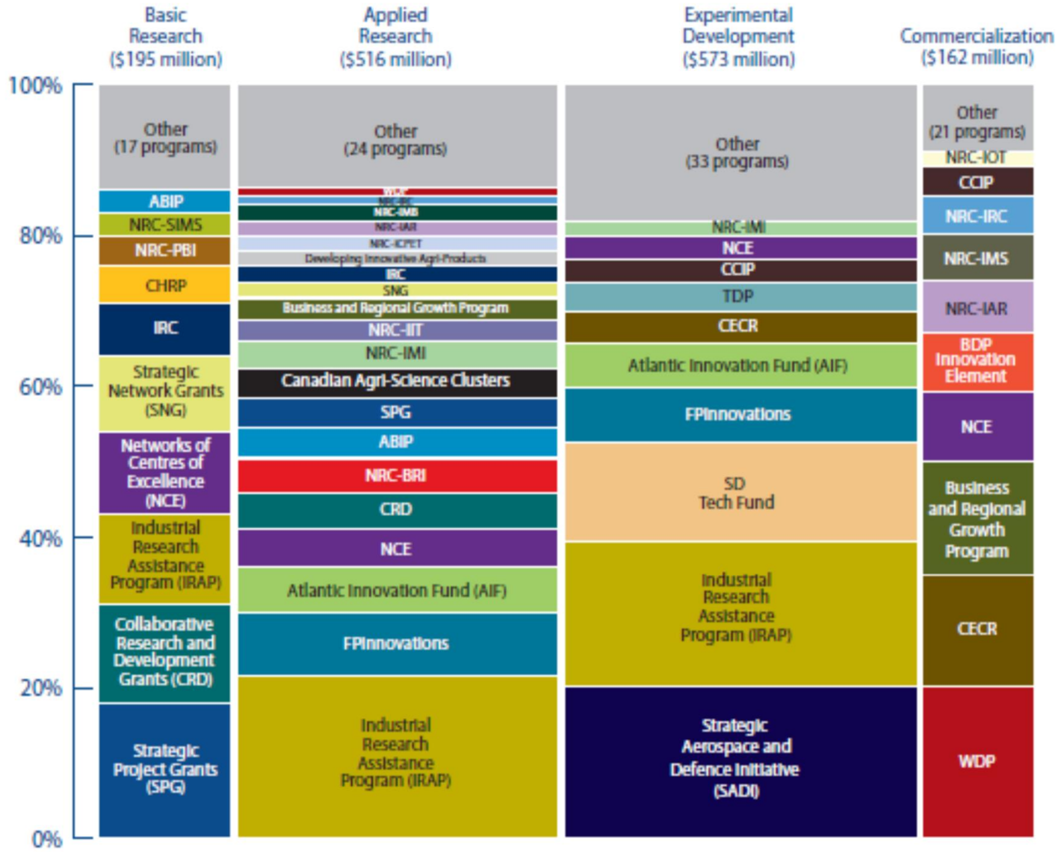

Fig. 2.18: Inventory of Direct Federal Government Innovation Support Programs in 2010
Source: Jenkins Report (2011)

Figure 2.18 illustrates the substantial complexity of Canadaôs direct support programs for basic and applied research, experimental development, and commercialisation. Other countries such as the United Kingdom have sought to reduce the number of programs offered and to help simplify government intervention in the national innovation system. Under the Solutions for Business program launched in 2011, the U.K. government consolidated the number of business support programs, and has substantially reduced the number of programs overall (Jenkins Report, 2011).

2.5.2: Policies Supporting University-Industry Research Collaboration

University-Industry Research Collaboration (UIRC) is an important channel for knowledge transfer within national innovation systems. It is an important mechanism for bringing new technological innovations to market, and for maximising the economic and social benefit from government investment in university research. A particular examination of government UIRC support programs is warranted given the topic of this study.

Prior to the 1980s, supporting UIRCs was not an important public policy concern for the Canadian government, possibly because of the low research intensity of Canadian firms, lack of pressure from international competition, focus on public sector research investment, or perceived political constraints on the federal government within the education sector. At the beginning of the 1980s, increased economic globalisation along with a greater focus on knowledge-based industries as a source of economic growth were the impetus for a greater focus on UIRCs support measures (Currie and Standards, 2011).

Since the late 1980s, UIRC has been highlighted as an increasingly important policy priority in government white papers, budgets and programs. The federal government views UIRC as one of many linkages to be encouraged within Canadaôs national innovation system. However, the government of Ontario has focused specifically on UIRC as a preferred mechanism for technology transfer in that province. In the United States, state and local governments have been leading the charge on UIRC advocacy, encouraging the development of regional networks and innovation clusters, although the U.S. federal government retains an important role as a UIRC funder. The United Kingdom was a particularly ardent advocate for UIRC in the 2000s. The Lambert Report of 2003 made strong recommendations to improve linkages between universities, firms and government, and led to the creation of the Technology Strategy Board to deliver UIRC programs. This was followed by the Hauser Report and the Dyson Report, which served as the basis for the U.K.ôs Blueprint for Technology in 2010 and the creation of Technology Innovation Centres (Currie and Standards, 2011).

The Canadian government spent more than CDN$370 million in 2010 on UIRC support through various programs, a considerable commitment relative to Canadaôs size. In comparison, the UK government spent over £1 billion from 2000 to 2010 on ñknowledge-based interactions between the higher education sector and organisations in the private, public and volunteer sectors, and wider societyò (Currie and Standards, 2011). Not surprisingly, U.S. government spending on research exceeds that of Canada and other countries considerably, especially in the fields of defense, health and energy. The National Science Foundation (NSF) encourages UIRC as part of its granting criteria. The Small Business Innovation Research (SBIR) program has been a much lauded success in encouraging UIRCs, and has prompted the adoption of similar programs in other countries.

In Canada, the most significant program to encourage UIRC at the federal level was the Networks of Centres of Excellence (NCE) program. Established in 1989, the NCE program supported the creation and development of research networks in key industries of strategic importance to the country. There were 20 NCEs in operation in 2010, and the government of Canada invested CDN$1.3 billion in the NCE program between 1989 and 2008 (Currie and Standards, 2011). The NCE program was actually based in part on a successful UIRC support program launched in the province of Ontario a few years earlier.

As education is a provincial responsibility in the Canadian federal system, some provinces have implemented research and innovation policies that complement those at the federal level (Liljemark, 2004). The government of Ontario has been particularly active in this regard, given the changes in the structure of Ontarioӳ economy in the 1980s and 1990s as described in Section 2.2. In particular, Ontario has enacted policies and programs that promote more knowledge-based industries within the provincial economy (Wolfe and Gertler, 2001). Among the most significant of these policies was the creation of the Ontario Centres of Excellence (OCE) program in 1987. Much like the federal NCEs that followed, OCE was created to build greater research capacity in industries of strategic importance to the province, and was given the explicit mandate to develop greater channels of knowledge transfer between universities and firms in Ontario. For over 30 years, OCE has evolved and endured governments of every political stripe, and has remained the centerpiece of Ontarioӳ policy in support of UIRC. A more complete discussion of OCE is provided in Section 5.4.

2.6: Knowledge Flows and Technology Transfer Channels

The efficiency and effectiveness of a national innovation system depends on the ӦFluidity of the linkages, particularly knowledge transfers, between the nodes of the systemӠ(Niosi, 2008).

Four broad types of knowledge flows exist within national innovation systems (OECD, 1997):

1. interactions among enterprises, primarily joint research activities and other technical collaborations;

2. interactions among enterprises, universities and public research institutes, including joint research, co-patenting, co-publications and more informal linkages;
3. diffusion of knowledge and technology to enterprises, including industry adoption rates for new technologies and diffusion through machinery and equipment; and
4. personnel mobility, focusing on the movement of technical personnel within and between the public and private sectors.ò

Through advanced research, universities ñmove the frontier of science forwardò, and transfer these research results to firms and society in general through channels such as highly qualified people, informal relationships, and more formalised collaborations like UIRC and research contracts (Niosi, 2008, Bramwell et al., 2012). Geiger (2012) provided a useful summary of common formal university-industry linkages:

Table 2.6: Common Formal University-Industry Linkages (Geiger (2012)

Individual Project	Institutional Links	Personal
• Contract research, deliverables • Unrestricted grants • Straight licensing • Sponsored research projects • Faculty consulting • Material transfer agreements	• Collaborative research in consortia • Participation in federal centres • Partnerships or alliances • Satellite laboratories	• Internships for students • Programs to support faculty • Graduate student support

UIRC is the form of linkage of particular interest in this study. However, it should be acknowledged that UIRC is only one of many formal and informal mechanisms, and that much of the most important knowledge transfer between universities and firms is ñtacit rather than codifiedò (Patel and Pavitt, 1994, Wolfe and Gertler, 2001, Perkmann and Walsh, 2007).

2.6.1: Sources of Innovation for Canadian Firms

Ghafele (Ghafele, 2012) argued that the knowledge generated by universities is ñthe ultimate source of competitive advantage in the marketplaceò when managed through formalised knowledge transfer mechanisms. Yet in Canada, domestic and foreign firms are in fact a more meaningful source of technology than universities (Niosi, 2008). The Jenkins Report (2011) also noted that only two percent of firms view universities as the most important source of innovation ideas.

Table 2.7: Percentage of Innovative Firms that Acquired License by Source from 2002-2004

Industry	Firms that Acquired Licences	CDN Firms	Foreign Firms	CDN Unis.	Federal Research Orgs.	Prov. Research Orgs.
Pharmaceuticals	36.9	72.7	76.3	21.8	-	-
Computers and electronic products	34.8	36.8	82.5	4.9	8.1	-
Aerospace products and parts	36.8	52.4	79.4	-	11.4	11.4
Transportation equipment	24.9	51.6	84.7	-	2.4	2.4
Manufacturing	16.9	53.4	66.2	2.7	4.3	2.5
Logging	7.4	n.a.	n.a.	n.a.	n.a.	n.a.
Food, beverages, and tobacco	15.2	49.5	52.0	-	20.7	21.4
Textiles	16.7	56.3	67.1	5.1	5.1	-
Clothing and leather products	17.0	51.0	76.8	-	-	-
Wood product manufacturing	13.4	84.9	21.2	-	8.9	-
Paper manufacturing	13.4	45.3	76.1	-	-	-
Printing and related activities	22.6	44.4	74.0	3.7	1.2	-
Petroleum and coal	31.8	53.2	100.0	-	-	-

products						
Chemical manufacturing	19.7	30.7	82.9	12.2	-	-
Chemicals (excluding pharma)	16.4	12.6	85.7	8.0	-	-
Plastics and rubber manufacturing	12.2	43.5	72.8	10.4	3.0	1.5
Nonmetallic mineral products	18.9	69.0	62.3	-	-	-
Primary metal manufacturing	22.7	68.6	53.7	15.6	3.3	-
Fabricated metal manufacturing	14.5	45.3	70.9	0.5	-	-
Machinery manufacturing	12.5	67.9	62.0	0.9	0.8	-
Electrical equipment, appliances	16.3	53.5	62.6	2.7	-	-
Furniture and related manufacturing	10.7	81.3	46.8	-	-	-
Miscellaneous manufacturing	19.3	66.3	53.3	-	-	-

Source: Statistics Canada (2006), as presented in Niosi (2008)

Overall, the Canadian pharmaceutical, ICT and aerospace sectors were the most significant licensors of technology in 2006. The pharmaceutical industryÕs reliance on licensing was not surprising given the high research intensity of that industry. Indeed, the biotechnology industry was responsible for 50 percent of all university patents, licenses, royalty income and startup companies in Canada and the United States (Mowery and Nelson, 2001). Among all sectors, the Canadian pharmaceutical industry was the most reliant upon universities as a source of licenses by a wide margin. However, even the pharmaceutical industry, and all other industries for that matter, were much more likely to license technology from other firms. In fact, firms in some important industries such as aerospace and transportation equipment (including automotive) did not license technology from Canadian universities at all. It would seem that Canadian firms prefer to collaborate on research and development with suppliers, customers and partners than with universities (Currie and Standards, 2011). Interestingly, this phenomenon is not isolated to Canada;

UIRCs in the United States and the United Kingdom also represent a relatively small portion of innovation knowledge flows in those countries (Hughes et al., 2006).

2.6.2: University-Industry Research Collaboration

Notwithstanding the findings above that universities play a secondary role as a source of technology in certain countries, firms are responsible for funding a larger proportion of the research undertaken at Canadian universities than are firms in other OECD countries, after controlling for differences in the size of national economies (Currie and Standards, 2011)[10].

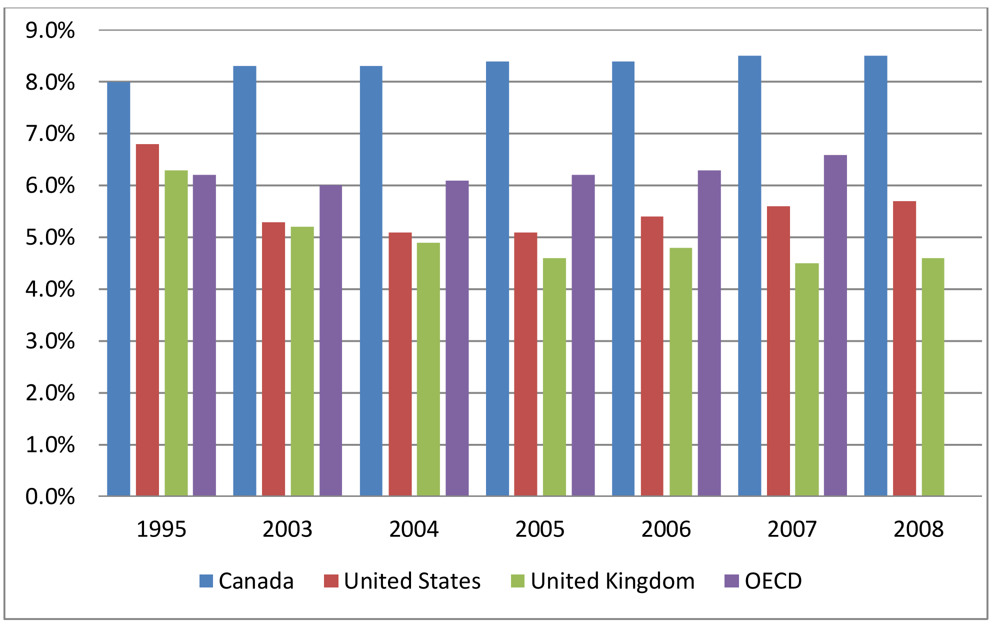

Fig. 2.19: Proportion of University Research Funded by Firms in Selected Countries
Source: Adapted from Currie and Standards (2011)

[10] Currie and Standards (2011) noted several challenges in the international comparability of HERD funding statistics definition of the sector, reporting thresholds, treatment of capital expenditures, accounting for indirect costs of research and others. Please see p. 58 of their report for additional information on the dataǒs limitations.

The average proportion of HERD in Canada that was funded by firms between 2003 and 2008 was 8.4 percent, which was considerably higher than the U.S. and U.K.ós averages of 5.4 percent and 4.8 percent, respectively. Canada ranked fifth among OECD countries on this indicator in 2004 (Niosi, 2008). The proportion of HERD funded by firms in these countries remained fairly consistent over the 2003-2008 period; it represented .06 percent of GDP in Canada, and .02 percent of GDP in the U.S. and the U.K. It should be noted that it was unclear to Currie and Standards (2011) the extent to which these differences were a result of different reporting practices across the countries, therefore the data should be interpreted with caution.

Interestingly, the share of BERD performed by universities is also significantly higher in Canada than in other comparable countries. The proportion of BERD performed by universities is 6.2 percent in Canada, but only 1.1 percent in the U.S. and 2.5 percent in the U.K. The difference between 1) the proportion of university research funded by firms, and 2) the proportion of firm research performed by universities is worth explaining in the Canadian context of this study:

1) University research funded by firms in Canada generally includes sponsored research grants and research collaborations that involve both university and firm participants. The aim of these UIRCs, which are often co-funded by government funding agencies like OCE, is applied but remains exploratory in nature. The contracts for these UIRCs do not generally provide assignment of ownership of the project IP to the firm, nor do they provide licensing rights to the firm to commercially exploit the project IP. In some cases, firms may receive an option or some other type of preferential access to project IP, but under terms to be negotiated after the project is completed, when the value of the results is more fully known. These are the type of UIRCs that are the subject of interest in this study.

2) Firm research conducted by universities can generally be defined as ñresearch contractsò, in which firms hire university researchers to accomplish specific research or technology development goals of interest to the firm. Firms typically fund these contracts without government co-funding. The contract may require assignment of ownership of the project IP to the firm or licensing rights to commercially exploit the project IP. These projects and their outcomes are not the subject interest in this study, however they represent an important mechanism of formal university-industry linkage that is worth of note but should be distinguished from the UIRCs described above.

Beyond the proportion of Canadian university research funded by firms, Canadaôs performance on other qualitative, opinion-based UIRC indicators is on par with other countries, such as the United States and the United Kingdom.

Table 2.8: Comparison of Canadian, U.S. and U.K. UIRC Performance Indicators

Indicator	Generalis-ability	Canada	US	UK
Share of total university research funded by firms (2008)	Medium	8.50%	5.70%	4.60%
R&D funded by firms and performed by higher education sector as % of GDP (2007)	Medium	0.06%	0.02%	0.02%
Share of total BERD performed by universities (2007)	Medium	6.20%	1.10%	2.50%
World Economic Forum country rankings on UIRC (2010)	High	7	1	4
WEF 10 yr. avg. score on UIRC (1= do not collaborate, 7 = collaborate extensively) (2001-2010)	High	5	5.6	5.1
IMD World Competitiveness Yearbook Country Ranking on knowledge transfer between firms and universities (2010)	High	8	2	15

Source: Adapted from Currie and Standards (2011)

Canada ranked 7th among countries with extensive UIRC activity in the World Economic Forumôs (WEF) 2010 survey of business opinion. Although Canada ranked behind the U.S. and the U.K., who respectively ranked 1^{st} and 4^{th}, it represented an improvement from Canadaôs ranking of 15^{th} in 2007. In fact, the average ranking of the three countries in the WEF survey between 2001-2010 was quite comparable. An alternative survey of business opinion conducted by the Institute for Management Development (IMD) ranked Canada 8^{th} on knowledge transfer between firms and universities in 2010, putting Canada behind the U.S. (2^{nd}) but ahead of the U.K. (15^{th}).

Canadaôs comparative performance on UIRC indicators, and the high level of university research funded by firms, suggested that Canadaôs track record or technology transfer and commercialisation outcomes should also be comparable or better than that of other countries. As discussed below, this was not the case and warrants explanation.

2.6.3: University-Industry Technology Transfer

A number of studies and reports have argued that Canadaôs technology transfer performance is poor relative to other countries, in particular the United States (Jenkins Report, 2011, Niosi, 2008). These studies have generally compared Canada and the U.S. in absolute terms, or using rough scaling measures such as ñper universityò figures that may not adequately control for the relative size and scale of activities in Canadian universities compared to others.

Currie and Standards (2011) applied robust scaling of various technology transfer performance indicators and found that ñthere is little evidence to conclude that Canada outperforms other comparator countries in deriving economic and social value from business spending on university-based research.ò Nor did their study conclude that Canada comparatively underperforms. Currie and Standardsô (2011) included indicators that measure both the ñcommercial potentialò and the ñcommercial applicationò of UIRC outcomes.

Table 2.9: Comparison of Canadian, U.S. and U.K. Technology Transfer Performance Indicators

Indicator	Generalis-ability	Canada	US	UK
University commercialisation staff per USD$100 million in research expenditures (Canada, US 2008; UK 2005)	Low	7.9	5	19.6
Indicators of Commercial Potential:				
Universities: Invention disclosures per USD$100 million in research expenditures (2004)	Medium	32	40.4	51.6
Universities: Patent applications per USD$100 million in research expenditures (2004)	Medium	29.7	25.5	15.1
Universities: Patent grants per USD$100 million in research expenditures (2004)	Medium	4.9	8.8	3.1
Indicators of Commercial Application:				
Universities: Licenses executed per USD$100 million in research expenditures (2004)	Medium	11.3	11	36.7
Universities: Startup companies formed per USD$ 100 million in research expenditures (2004)	Medium	1.5	1.1	2.8
Universities: Licence Revenues as percent total university research expenditures in 2004	Medium	1.00%	2.90%	1.10%

Source: Adapted from Currie and Standards (2011)

Among technology transfer indicators of ñcommercial potentialò, Canadian universities generated considerably fewer invention disclosures compared to the U.S. and the U.K. The U.K. ranked highest in disclosures but lowest in patents granted at 3.1 patents per USD$100 million in research expenditures. Canada fared slightly better at 4.9 patents granted but trailed considerably behind the U.S. at 8.8 patents granted.

With regard to technology transfer indicators of ñcommercial applicationò, licensing technology to existing firms has traditionally been the most popular mechanisms of technology transfer. Technology Transfer Offices (TTOs) within universities in North

America and Europe were largely designed to facilitate licensing (Wright et al., 2008). In most Canadian universities, researchers, student and staff are required to disclose all inventions to the universityôs TTO. The TTO evaluates disclosures and decides which should be protected through patents, copyright, industrial design, or other forms of protection. The inventor and the university may then come to an agreement on the division of royalties, if the division is not spelled out in the universityôs IP policy. The TTO then begins the search for potential licensees (Niosi, 2008). The productivity of university licensing is influenced by several factors, including the size and capability of TTOs and the incentive mechanisms designed for academic scientists (Bramwell et al., 2012). U.K. universities had almost 2.5 times more commercialisation staff per $100 million in HERD than Canadian universities, and almost four times more than U.S. universities. Therefore, perhaps not surprisingly, the U.K. and other European Union countries ranked highest in licenses executed and startups formed, with Canada ranked second but only slightly ahead of the U.S. However, the U.S. led all countries in license revenue as a percentage of HERD (Currie and Standards, 2011).

Startups are the university technology transfer outcome that has attracted the most significant policy attention in Canada. When relatively low research intensity, absorptive capacity, and size of Canadian firms translates into relatively few receptors for technology licenses, startups are an attractive alternative, especially if the researchers or students involved in creating the core intellectual property are interested in participating. However, there is considerable debate about the effectiveness of startups as a technology transfer mechanism (Lockett et al., 2005, Bramwell et al., 2012). Currie and Standardsô (2011) analysis is consistent with Clayman (2003) who also found that Canadian universities created considerably more startups per dollar of research compared to U.S. universities.

There exists a major difference between the Canadian and the U.S. and U.K. university technology transfer systems that may be a cause for under-representation of Canadaôs performance relative to these jurisdictions. In the U.S., the Bayh-Dole Act of 1980 mandated that inventions created at universities using public funds would be owned by university, in order to facilitate their commercialisation.

In the U.K., the traditional concept of ñProfessorôs Privilegeò, which granted IP ownership rights to university researchers, has largely been abandoned (Geuna and Rossi, 2011). In fact, 87 percent of U.K. universities claim ownership of intellectual property as a matter of policy (Gadd, 2017). In Canada, each university has adopted its own unique intellectual property ownership policy. In Ontario, 89 percent of universities have adopted inventor-owned intellectual property ownership policies (Hen, 2010).

These differences in policy have two important implications for understanding Canadaôs relative technology transfer performance. First, as described above in Section 2.6.2, Canadaôs universities perform a considerably larger proportion of BERD as ñresearch contractsò that the U.S. and the U.K. Much of the intellectual property, including any patents, resulting from these contracts is assigned directly to the contracting firms, bypassing the university entirely. Several studies found similar results in Europe, although the proportion of ñresearch contractsò is lower in that country than in Canada (Crespi et al., 2006, Geuna and Nesta, 2006). In contrast, over 62 percent of the patents invented at top U.S. universities were assigned to the university, while only 26 percent were assigned solely to firms (Niosi, 2008). It is important to understand that the technology transfer created through ñresearch contractsò goes largely unnoticed. Most technology transfer metrics are concerned with measuring technology owned by universities or transferred to firms by universities, which ñignores the sub merged part of the iceberg of technologiesò that are transferred directly to firms or not protected via patent or other means by universities (Niosi, 2008).

Second, because Canada lacks a Bayh-Dole style policy framework that governs the system-wide ownership and management of university intellectual property, an unknown proportion of the commercialisation outcomes from Canadian universities goes unreported or slips through the cracks. The majority of Canadian universities have adopted inventor-owned intellectual property ownership policies. Although those policies still require inventors to disclose their inventions, there is little incentive for inventors to do so if the university is not otherwise involved in the commercialisation process. Therefore, some commercialisation outcomes go unreported in the technology transfer metrics collected and reported by universities.

2.7: Summary

This chapter explores the institutions, policies and linkages that form Canadaôs national innovation system. It has important implications for putting this studyôs findings and policy recommendations in the context of the Canadian system and that of other jurisdictions like the United States and the United Kingdom. The key points are summarised below:

- Canada has strong economic, political and cultural ties to both the United States and the United Kingdom. In that sense, Canada has one foot in the traditions of each of these countries, which makes them interesting comparators after controlling for the relative size and scope of each system.

- Within goods producing industries in Canada, resource exploitation plays an important role due to the abundance of resources. Ontario is Canadaœs manufacturing heartland with particular strength in transportation services (automotive and aerospace) and Information and Communications Technologies (ICT). Manufacturing sales declined in Canada from 1999 to 2009, while the ICT sector grew in relative importance over the same period, underscoring a structural shift from industrial to knowledge-based industries.
- Canada has invested considerably less in research and development as a proportion of GDP than many other OECD countries, which is largely attributable to low firm research intensity and suggests low absorptive capacity among Canadian firms. However, this is also largely due to differences in the research intensity of key Canadian industries compared to other countries. Research intensity was highest in the Canadian ICT sector and was considerably higher than that of U.S. ICT firms, but was research intensity was negligible in the Canadian automotive sector.
- Other unique factors influence the research intensity of Canadian firms. The Canadian economy is characterised by an increasingly high degree of foreign ownership, by the U.S. in particular. Correspondingly, Canada has a comparatively low number of large firms in knowledge-based industries, as many promising firms in these sectors are acquired by U.S. and other foreign multinationals before they achieve significant scale.
- Canadaœs expenditures on university research are second highest in the OECD relative to GDP. However, there is vast disparity in the scale, reputation and commercialisation output of Canadian universities. Only three universities in Ontario could be considered ñworld-classò.

- Canada has among the highest rates of government support for firm research and development in the world. Indirect tax incentives represent the vast majority of this support, and a complex myriad of direct support programs also exists. Sector-based initiative such as the Canadian Networks of Centres of Excellence (NCE) and the provincial Ontario Centres of Excellence (OCE) are among the most important direct UIRC support programs.
- Firms in Canada, the U.S. and the U.K. prefer to collaborate on research with other firms than with universities. However, firms fund a relatively higher proportion of Canadian university research, and Canadian universities perform a relatively higher proportion of firm research, compared to the U.S. and the U.K.
- Although the technology transfer performance of Canadian universities is generally considered poor relative to other countries, Canadaǿs performance may actually be comparable to the U.S. and the U.K. when appropriately controlling for the scale and policies of each university system.

The Canadian innovation system is unique in a number of ways: its geography, socio-economics and political history; the composition and low research intensity of its industries; the structure and policy environment of its universities; the lack of large firms and high degree of foreign ownership; and, the high relative importance of university research to the country and its firms. Yet, Canada shares a number of similarities with other countries, such as the United States and the United Kingdom: its democratic institutions and other cultural bonds; the growing importance of the service sector and transition from industrial to knowledge-based economies; policies to encourage linkages between universities and firms; and, the relative technology transfer performance of universities. There is, indeed, a basis upon which the findings and policy recommendations in this study may be relevant to other comparable innovation systems and countries. However, generalisation of the results should be done with caution and on a case-by-case basis. This will be considered further in Chapter VIII: Discussion.

Finally, this assessment of the Canadian national innovation system informs the following review of the related academic literature, and of the prevailing theories that seek to explain many of the features that underpin the Canadian system.

CHAPTER III: LITERATURE REVIEW

Chapter II discussed the role of researchers, firms, universities and government policy in Canadaôs national innovation system and the impact that these stakeholders have on the commercialisation of university-industry research collaborations (UIRC). This chapter reviews the literature on UIRC and technology transfer to define our current understanding of how the characteristics of these stakeholders contribute to why some UIRCs generate more commercial results than others. The goals of the chapter are 1) to describe current theories about what factors lead to successful UIRCs, 2) to determine what characteristics were used in previous studies of commercialisation from UIRCs, and 3) to identify what new knowledge this study can contribute to an increasingly important field of research.

3.1: Introduction

This study explores the relationship between the characteristics of the stakeholders in UIRCs and the commercialisation of their results. Therefore, it lies at the intersection of two fields of study: 1) university research and development (R&D), including UIRCs in particular, and 2) the literature on university technology transfer and commercialisation. Accordingly, Section 3.2 describes, in broad terms, the body of literature in each field of study, and discusses how this study attempts to bridge an important gap between them.

There is a vast collection of literature on UIRCs and university technology transfer, some of which is more relevant to this studyôs research topic than others. Consequently, Section 3.3 of this chapter describes two useful organising frameworks for the literature, one in each of these two fields, to help set the boundary conditions for the literature review.

As described in Sections 2.4 and 2.6, researchers play a particularly important role in Canadaôs university system. Canadian research granting agencies, such as the Ontario Centres of Excellence, award grants at the individual researcher level, not at the university level. Also, the vast majority of universities in Canada have inventor-owned intellectual property ownership policies. These factors put the researcher in the driverôs seat of both the research agenda and the commercialisation of research results. As a result, Section 3.4 of this chapter discusses previous studies of researcher productivity and quality, outlines the challenges associated with these measures, and suggests the emerging concept of researcher ñembeddednessò as a more practical alternative.

Section 2.3 discussed the low research intensity of Canadian firms, caused in part by the high degree of foreign ownership and the lack of large knowledge-based companies. Hence, Section 3.5 of this chapter explores what the literature tells us about the role of firm characteristics in research collaboration and commercialisation, and the theory of how a firmôs research intensity affects its absorptive capacity.

Section 2.2 discussed the ongoing shift in Canadaôs economy, and in that of other comparable countries, from traditional manufacturing industries to knowledge-based industries. Section 2.3.3 also outlined how the low research intensity of Canadian firms can be explained by sectoral differences. Thus, Section 3.6 of this chapter discusses prior studies on how the projectôs field of research may affect the commercialisation of its results.

A number of other stakeholder characteristics should be controlled for that may affect the commercialisation of UIRC results. Section 3.7 of this chapter explores other empirical studies with independent variables related to UIRC stakeholder characteristics, or the characteristics of the UIRCös structure.

3.2: Bridging the Gap between UIRC and Technology Transfer Literature

The study attempts to bridge the gap between the literature on university research and development and the literature on university technology transfer by exploring how the characteristics of later-stage, formal UIRCs are associated with the early stages of commercialisation.

Figure 3.2 illustrates the gap in the literature and how the study attempts to address it. It contains two mirrored triangles with the bottom triangle representing the literature on university research and development and the top triangle representing the literature on university technology transfer and commercialisation. Each triangle is divided using important themes found in each body of literature, and they are meant to be interpreted from bottom to top. The bottom triangle on research begins with broad national innovation systems as the base, and becomes progressively more focused on the universityös role in informal and formal knowledge sharing networks, then on UIRC projects in particular, and finally on the project outcomes. The top triangle on technology transfer begins with the invention disclosures as the starting point and the fuel for the technology transfer process, then progresses to patenting on the way to licensing or startup creation, with the magnitude of the opportunity, the potential impact, and the investment required increasing at each step.

University R&D and university technology transfer are often treated as disparate processes in the academic literature, delineated by the point of invention: university research generates new knowledge that may lead to inventions; university technology transfer converts inventions into licenses and startups.

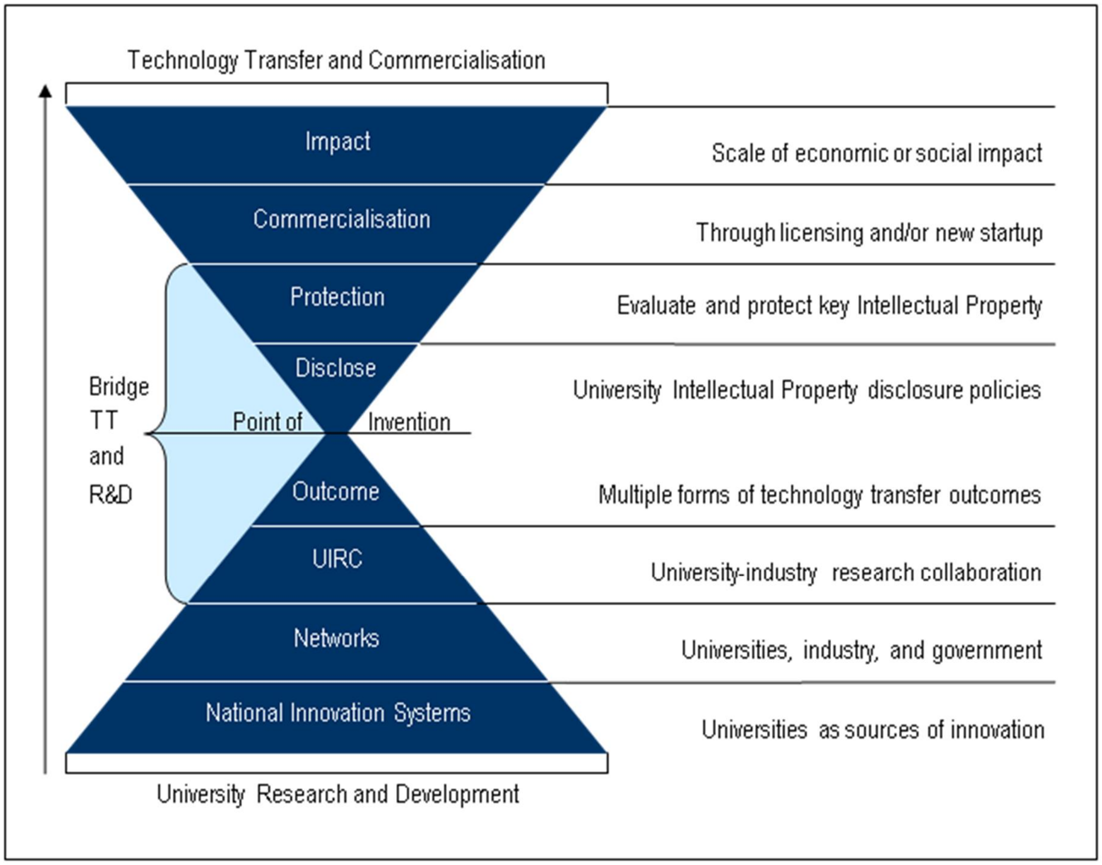

Fig. 3.1 University R&D and Technology Transfer Literature

3.2.1: University Research and Development Literature

Numerous empirical studies have demonstrated the positive impact of research and development on growth and productivity at the firm, industry and national level (Arrow, 1962). Typically, the production, diffusion, adoption and mastery of technology are undertaken by firms. However, a complex system of institutional players and policies is required to promote innovation activity at a system level, and to create linkages and facilitate interaction among the players (Niosi, 2008). Universities are key players in this system and while they were once focused exclusively on research and teaching, today they are increasingly being asked to take on an important ñthird missionò of facilitating technology transfer.

National Innovation Systems: National innovations systems are social constructs that seek to explain how organisations, institutions, government policies and the linkages between them influence the creation and diffusion of technology in different countries (Niosi, 2008). The idea of a national innovation system was first mentioned by Freeman (1987) in his study of innovation in Japan. The concept was laid out in detail in four chapters (Freeman et al., 1988, Lundvall et al., 1988, Nelson, 1988, Pelikan, 1988) of *Technical Change and Economic Theory* (Dosi et al., 1988). The concept was further expanded upon by Lundvall (1992), who described the informal linkages and networks that support knowledge transfer between organisations. Conversely, Nelson (1993) highlighted the rules and structures that govern institutional behaviour and influence knowledge transfer. Chapter II provided a detailed analysis of Canadaôs national innovation system, including the unique relationship between Canadian universities and firms, and the policies enacted by governments to stimulate greater technology transfer between them.

Networks: Freeman (1987) emphasised the role of political and social institutions in national innovation systems. Several theories have since attempted to characterise the networks and relationships between universities, firms and government (Azagra-Caro, 2007). The Mode 2 knowledge production model (Gibbons et al., 1994) explained how organisations interact to form interdisciplinary teams that collectively address applied, real world problems.[11] The Triple Helix model (Leydesdorff and Etzkowitz, 1996) described the ongoing shift from a dyadic industrial economy dominated by industry-government interactions to a triadic knowledge economy governed by university-industry-government interactions. Some of the most important knowledge transfer between universities and firms is ñtacit rather than codifiedò (Patel and Pavitt, 1994, Wolfe and Gertler, 2001, Perkmann and Walsh, 2007).

University-Industry Research Collaboration: As described in Section 2.5.2, universities and firms collaborate in a number of ways, with varying levels of formality. Many of these interactions are random because they are governed by a complex set of social, political and economic forces. However, some of the interactions are more ñrule-likeò because they are governed by specific laws, regulations, policies or programs (Katz, 2006). Indeed, there is wide disparity in the literature on what should be considered ñresearch collaborationò (Bozeman et al., 2013). Research contracts funded entirely by firms represent a large proportion of ñformalò collaborations between Canadian universities and firms. These research contracts typically involve the direct assignment to the firm of the knowledge or technology created, which may or may not be captured in the technology transfer metrics commonly collected by Canadian universities. UIRC projects that are at least partially funded by government agencies are a distinct type of formal collaboration because the interaction and knowledge transfer between universities and firms is constrained based on the mandate of the specific government funding

[11] In contrast, Mode 1 knowledge production is curiosity-driven and motivated by the pursuit of greater knowledge.

program. These types of UIRCs are the subject of interest in this study, and embody the complex university-industry-government interactions at the heart of the Mode 2 and Triple Helix models.

UIRC is on the rise in almost every field of scientific and technical research (Beaver and Rosen, 1979). The extant literature on UIRC is generally concerned with theories that explain the incremental difference in the outcomes that result from research collaboration compared to working alone (Bozeman et al., 2013). Subramanyam (1983) was among the first of many studies to find that research collaboration increased productivity. Other studies soon followed that focused primarily on how research collaboration increases the production of new knowledge, in what Bozeman (2013) called ñknowledge-focusedò collaborations. Pravdiĺ and Oluiĺ-Vukoviĺ (1986) first found a strong relationship between scientific output in the field of chemistry and the frequency of collaboration between the same individual researchers and groups of researchers. Later, Lee and Bozeman (2005) found a strong association between the number of publications produced and the number of individual collaborators. However, the number of collaborators was not a significant predictor of publishing productivity when considering the ñfractional countò of the number of publications divided by the number of authors.

Outcomes: A much smaller subset of UIRC studies are concerned with the influence of collaboration on more tangible outputs such as patents, licenses and startups, in what Bozeman (2013) called ñproperty-focusedò collaborations. Hanel and St-Pierreôs (2006) study of UIRCs in the Canadian manufacturing industry found that collaboration increased the novelty of the innovations produced and improved the firmós perception of their economic performance. Adams et al. (2003) found that UIRCs stimulated patenting by firms much more effectively than other technology transfer mechanisms. Ambos et al.ós (2008) study of UIRCs in the United Kingdom explored the tension between academic and commercial activities at U.K. universities. They found that the researchers involved in collaborations that produce academic outcomes have different characteristics than researchers who produce commercial outcomes.

3.2.2: University Technology Transfer Literature

There is a rich body of research in technology transfer reaching back over 50 years. The term technology transfer originated in the field of economics; however the definition and very concept of technology transfer can differ significantly across the fields of study, including economics, sociology, anthropology and management. Zhao and Reisman (1992) were the first to conduct an integrative review of the technology transfer taxonomies in each stream of knowledge.

Broadly speaking, technology transfer can be defined as ñthe movement of know-how, technical knowledge, or technology from one organisational setting to anotherò (Bozeman, 2000).[12] Most research on technology transfer examines the factors that influence the effectiveness of technology transfer through different mechanisms and the impact of technology transfer on the organisations involved. Implicitly, the mechanisms of technology transfer are highly dependent on the organisational setting. This study is

[12] Bozeman (2000) p. 629 attributes this definition to Roessner in an unknown paper.

concerned entirely with the transfer of technology from universities to firms. University technology transfer research has exploded since the 1980s, especially in the United States, fueled by increased activity generated by policy initiatives such as the Bayh-Dole Act of 1980, and the related technology transfer data collected by the Association of University Technology Managers (AUTM) (Bozeman et al., 2015).

Disclose: In practice, the technology transfer process at universities begins with the disclosure of inventions by faculty, students and staff. Invention disclosure rules are typically outlined in each universityøs Intellectual Property (IP) policy, although a faculty memberøs decision to disclose is also influenced by the perceived benefits of patenting the invention (Owen-Smith and Powell, 2001b). However, Thursby and Thursby (2002) found an increase in the overall propensity of faculty members in U.S. universities to disclose inventions and apply for patents. In the U.K., the view on invention disclosure is articulated in one of Raynerøs (2013) four *Oxford Principles*, which encourages public disclosure of research results as a matter of public good. A number of studies have explored the factors that influence the number of invention disclosures received by a university. Friedman and Silberman (2003) found that the quality of a universityøs faculty is positively associated with the number of invention disclosures. Thursby and Thursby (2005) found that female faculty members are less likely to disclose inventions than males, after controlling for several factors.

Protection: Inventions are evaluated for their market potential and may be protected by patent, copyright, trade secret, or other mechanisms. Patents ñmark the certification of an inventionò (Acs et al., 1994, p. 337) and are an important indicator of its commercial potential (Currie and Standards, 2011). Especially in the U.S., university inventions are generally evaluated and protected by university Technology Transfer Offices (TTOs). It is important to understand that patents are an intermediate step towards technology transfer. Using the Massachusetts Institute of Technology as a model, Agrawal and Henderson (2002) found that the number of patents alone did not adequately describe a universityøs impact on the economy, or the nature of the knowledge the university created and transferred to other organisations. A number of studies have explored the factors that influence the number of patents filed based on university inventions. Mowery et al. (2001) cited the considerable impact of the Bayh-Dole Act among other factors that have contributed to the overall increase in university patenting in the U.S. Also not surprisingly, Powers (2003) found that universities with older TTOs, higher quality researchers and higher research budgets produce more patents. Swamidass and Vulasa (2009) found that smaller TTOs with limited staff and budgets focus more on filing patents rather than licensing technology.

Commercialisation: As described in Chapter II, licenses and startups are among the most important university technology transfer mechanisms. Formal commercialisation is typically implemented by licensing inventions to existing firms or by creating new firms with the purpose of commercialising inventions (Bozeman et al., 2013). Licenses have traditionally been the most important measure of a universityøs technology transfer performance. However, university startups have been of increasing interest to policy makers in Canada and in other countries. González-Pernía et al. (2013) noted that licenses and startups ñare not always equally suitable to align the incentives of universities, industry, and faculty in the quest for knowledge transferò. Indeed, Ismail et al.ôs (2015) study of a Scottish university found a number of factors that can affect the mechanism selected to commercialise inventions. They found that the decision to create a startup was influenced by the inventorôs level of motivation and perception of the inventionôs commercial potential, while the decision to license could be driven by the inventor, the firm or the university. Licenses and/or startups serve as dependent variables in a large number of studies of university technology transfer, many of which will be explored later in this chapter.

Impact: Following the execution of a license or the creation of a startup, a considerable investment of capital and other resources may be required by firms to develop inventions into new products and services, to integrate inventions into existing products and services, and to bring these products and services to market. Relatively few university technology transfer studies assess the factors associated with the magnitude of the economic or social impact of individual licenses or startups (Bozeman et al., 2015). The most popular impact criterion used in the literature is what Bozeman (2000) called the ñout-the-doorò criterion, which simply measures the occurrence of a license or a startup. The practicality and convenience of this measure of impact is obvious, but it also appropriately reflects the inventor and the universityôs ñdomain of controlò (Bozeman et al., 2015). For example, the inventor and the university may have very limited control over how a licensee firm develops the final product and brings it to market. However, these factors would influence the commercial impact of the technology transfer considerably. Therefore, it may be problematic to attribute the magnitude of the economic or social impact of a license or a startup to the inventor or the university.

3.2.3: Bridging the Gap

As described above, university R&D and university technology transfer are often treated as disparate processes in the academic literature, delineated by the point of invention. However, the intent to commercialise can begin at the research phase, before the point of invention. UIRCs are prime examples of this, since they are focused on applied, industrially-relevant research that may aim to achieve commercial outcomes. Also, in the case of government supported UIRCs, they are typically structured to facilitate the transfer of technology to collaborating firms. In cases where resulting technology is not adopted by collaborating firms, it may still be attractive to other firms because it was conceived with an industry need in mind. Therefore, this study bridges the gap by exploring how the characteristics of the stakeholders in later-stage applied research collaborations are associated with early-stage commercial outcomes.

Ambos et al. (2008) was the only study found that specifically examined the likelihood of commercial outcomes with UIRCs as the unit of observation. Consequently, it is of considerable importance to the design and methodology of this study. Using 207 U.K. research council-funded UIRC projects, Ambos et al. (2008) investigated the relationship between organisation-level and individual-level attributes of UIRCs and the likelihood of generating patents, licenses or startups. Ambos et al.ôs (2008) treatment of commercial outcomes from UIRCs has important implications for this study.

First, Ambos et al.ôs (2008) dependent variable measured patent, license and startup counts. There was no consideration of the magnitude or impact of the commercial outcome; their study only counted if one of these outcomes occurred or not. As described above, this treatment is also consistent with Bozemanôs (2000) ñout-the-doorò criteria for technology transfer success.

Second, Ambos et al. (2008) used a dichotomous dependent variable. All projects that generated a patent, license or startup were coded as (1) while those that did not were coded as (0). ñOur broad measure of commercial outputs did not allow us to reveal potential differences between the conditions leading to patenting, licensing and spin-out activities.ò ñFuture research might, however, usefully look at the different conditions that give rise to each different activity.ò (Ambos et al., 2008, p. 1443)

Ambos et al. (2008) was concerned primarily with how the tension between commercial and academic outcomes creates ambidexterity within research institutions and with individual researchers. Therefore, the methodology and independent variables were designed to ñdraw some inferences about the extent of (organisational and individual) ambidexterity in academiaò (Ambos et al., 2008, p. 1429), not to explore the effectiveness of commercialisation from UIRCs. Nevertheless, Ambos et al. (2008) reached a number of important conclusions that inform this study.

First, Ambos et al. (2008) developed the concept of a researcherôs ñembeddednessò in academia based on previous studies that examined the role of human and social capital accumulation in the formation of scientific careers. Those studies suggested a split between the predisposition of ñnew-schoolò and ñold-schoolò researchers towards academic entrepreneurship. Ambos et al.(2008) argued that the more a researcherôs experience, competencies, relationships and ways of thinking are geared to academia, the lower the likelihood that they will possess or develop the competencies required to produce commercial results. Indeed, their study found that researchers who deliver commercial outcomes were different than those more accustomed to producing academic outcomes. In fact, they found that commercial outputs were more likely in UIRCs where the Principal Investigator was not a professor, and had fewer years of experience since earning their PhD.

Second, Ambos et al. (2008) investigated the impact of a firmǿs cash contribution to a UIRC on its commercial outcome. In fact, it was the only firm characteristic used in their study. Ambos et al. (2008) acknowledged the potentially important difference between cash contributions to UIRCs and in-kind contributions, such as staff time, equipment or access to facilities. Since in-kind contributions are more ñparticipativeò in nature, their effect on UIRC commercialisation may be different than cash contributions. Ambos et al. (2008) included a measure of whether or not the firm had dedicated cash to the UIRC. Their study found no significant relationship between the presence of a cash contribution by the firm and a commercial outcome.

Third, Ambos et al. (2008) recognised that commercial outcomes from UIRC may be different in various fields of research based on previous studies that showed how engineering disciplines differed from natural sciences. Interestingly, Ambos et al. (2008) found no significant relationship between the commercial outcomes of UIRCs in different sectors. This is particularly important for this study, given the considerable differences in research intensity within certain sectors of the Canadian economy.

Ambos et al. (2008) will be explored in more detail as part of the upcoming discussion on the existing theories that seek to explain why some UIRCs are more successful than others. It will also be further explored in later chapters on methodology, results and discussion.

3.3: Organising the Literature Review

As described above, this study attempts to bridge the gap between prior studies on university-industry research collaboration, and those on university technology transfer by exploring how the stakeholders and structure of UIRCs are associated with the initial commercialisation of project results. Two different organising frameworks were used, one in each field of study, to help set the boundary conditions for the most relevant literature to be reviewed.

3.3.1: University Research Collaboration

In their comprehensive review of the literature on university research collaborations, Bozeman et al. (2013) state that ñthere is abundant evidence that research collaboration has become the norm in every field of scientific and technical research.ò The study goes on to define research collaboration as the ñsocial processes whereby human beings pool their human capital for the objective of producing knowledgeò.

Bozeman et al. (2013) proposed the following framework for organising the literature in the field of university research collaboration (Figure 3.2):

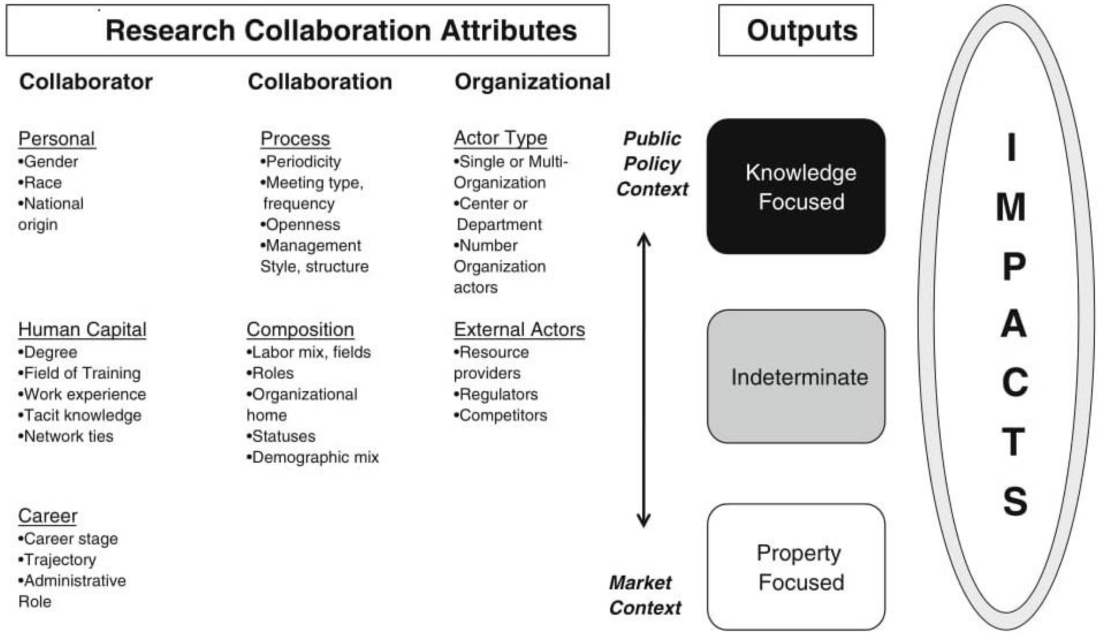

Fig. 3.2: Bozeman's Framework for Organising Research Collaboration Literature

The ñResearch Collaboration Attributesò shown in Figure 3.2 are relevant to the studyôs right hand side variables, while the ñOutputsò are relevant to the studyôs left hand side variables.

Bozemanôs framework identified three distinct categories of research collaboration attributes found in the literature: 1) the attributes of the collaborators themselves; 2) the attributes of the collaboration; and 3) attributes of the organisation or institution involved in the collaboration.[13]

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[13] Alternatively, DôEste and Perkmann (2011) identified four main motivations for undertaking UIRCs that are generally consistent Bozemanôs (2013) outcome categories.

Collaborator Attributes: Many studies examine the individual personal and professional characteristics of the collaborators. In the context of this study, this would include the characteristics of the academic researcher involved in the UIRC. Therefore, studies that included researcher attributes were reviewed.

Organisation/Institution Attributes: Some studies explore the characteristics of the organisations or institutions involved in the UIRC. Studies that explored the characteristics of university and firms were reviewed.

Collaboration Attributes: A number of studies investigate the characteristics of the collaboration itself, including how the UIRC is structured and managed. Studies that investigated the characteristics of the project structure were reviewed. However, studies focused on project management or on factors measured after the start of the project were not reviewed due to the *a priori* nature of the independent variables in this study.

Bozeman et al. (2013) also identified two distinct types of UIRCs investigated in the literature, based on their intended outcomes: 1) collaborations that seek to expand the knowledge base in the field of study and enhance the researchersô academic reputations and careers (knowledge-focused research collaborations); and 2) collaborations that seek, at least in part, to produce economic value and wealth for the researchers (property-focused research collaborations).

Knowledge-Focused Research Collaborations: This literature defines new scientific or technical knowledge as the primary outcome. Outcomes are generally measured based on the number and quality of the scholarly publications produced and cited.

Although knowledge-focused outcomes are clearly important, they are not a subject of interest in this study.

Property-Focused Research Collaborations: Bozeman (2013) found that much of the property-focused literature deals with UIRCs specifically. However, they are most often measured in terms of new patents. The UIRCs supported by OCE are property-focused by their nature but measure outcomes in terms of licenses and startups. Therefore, studies that include property-focused outcomes from UIRCs were reviewed.

Bozemanõs framework for organising the research collaboration literature was important to the design of this study in two ways. First, it clarified the distinction between knowledge-focused and property-focused UIRCs, helping to sharpen the focus of this study on licenses and startups as understudied ñproperty-focusedò outcomes from UIRCs. Also, the framework distinguished between individual-level and institution/organisation-level attributes and emphasised the importance of each to our understanding of the phenomenon.

3.3.2: Technology Transfer and Commercialisation

In his review of university technology transfer, Bozeman (2000) proposed the Contingent Effectiveness Technology Transfer Model for organising the technology transfer literature (Figure 3.3). The model illustrates the heterogeneity of university-industry interaction and the multiple success criteria for technology transfer that can be used by different stakeholders.

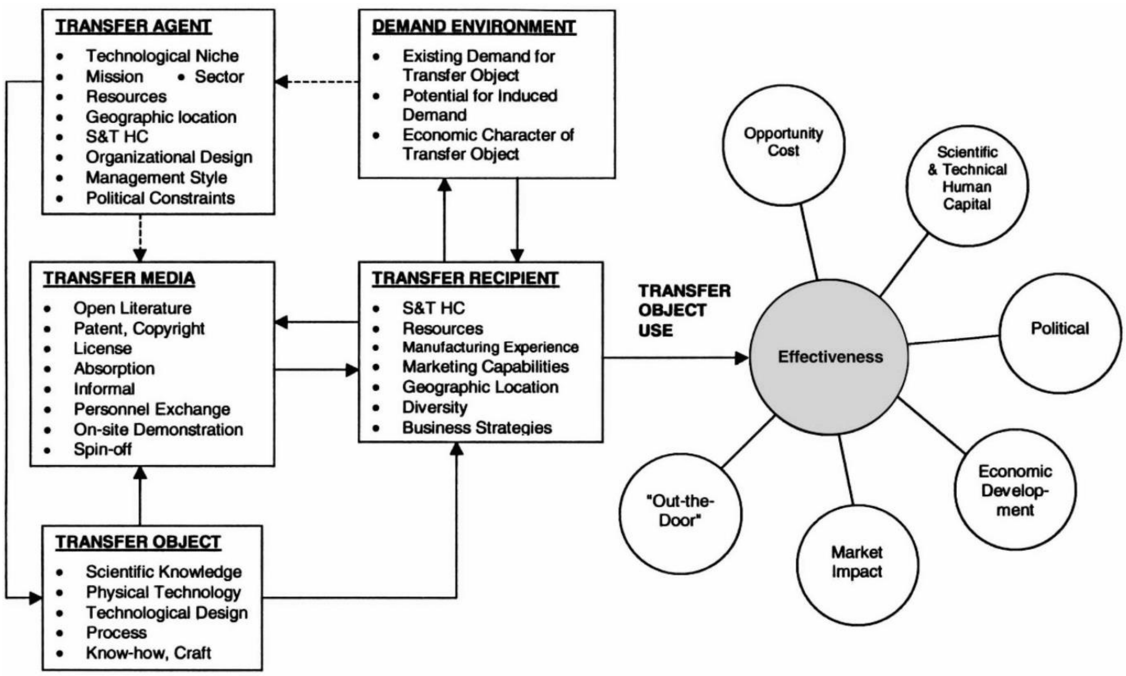

Fig. 3.3. Bozeman's Contingent Effectiveness Model of Technology Transfer

Bozemanǒs (2000) model included five broad determinants of effective university-industry technology transfer: 1) the characteristics of the transfer agent; 2) the characteristics of the transfer media; 3) the characteristics of the transfer object; 4) the demand environment; and 5) the characteristics of the transfer recipient.

Bozeman (2000) contended that there is no universal measure of technology transfer effectiveness. His model proposed six different, even contradictory[14], criteria for success:

[14] For example, the ňout-the-doorŏ concept is only concerned with whether technology transfer has occurred, while the ňmarket impactŏ concept is entirely concerned with the commercial impact of the technology transfer.

"Out-the-Door": Based on the fact that one organisation has received the technology provided by another, with no consideration of its impact. However, it has been argued that such a measure reflects only technology transfer ñactivitiesò rather than meaningful outcomes (Roessner, 2002).

Market Impact: Based on the commercial impact that resulted from the transfer, such as a product, profit or market share change.

Economic Development: Similar to Market Impact but gauges effects on a regional or national economy rather than a single firm or industry.

Political Reward: Based on the expectation of political reward flowing from participation in technology transfer.

Opportunity Cost: Examines not only alternative uses of resources but also possible impacts on other missions of the transfer agent or recipient.

Scientific and Technical Human Capital: Considers the impacts of technology transfer on the enhancement of scientific and technical skills, technically-relevant social capital, and infrastructures supporting scientific and technical work.

Bozemanôs Contingent Effectiveness Model of Technology Transfer helped to focus the literature review in two ways. First, it clarified the role and perspective of key stakeholders in technology transfer. Bozemanôs model considers the transfer agent and the transfer recipient as the two primary stakeholders in technology transfer. In this study, they represented the university and the firm, respectively. Therefore, the literature review included studies that explored the impact of university and firm characteristics on technology transfer. Although implicit within Bozemanôs model, researchers are also important stakeholders that have their own set of objectives and characteristics (Jensen et al., 2003). In fact, Bozeman (2013) found a large hole in the literature addressing the personal and social attributes of the individual scientists that influence research collaboration. Therefore, studies that included the characteristics of individual researchers were also reviewed. Studies that included the characteristics of the projectôs structure were included to represent the perspective of government as fourth stakeholder group, since the UIRCs under observation in this study are funded by a government agency (Ontario Centres of Excellence).

Second, Bozemanôs model suggests that each stakeholder may have a different definition of successful technology transfer, and their own criteria for whether or not success was achieved. Bozemanôs ñout-the-doorò criteria is consistent with this studyôs measurement of the occurrence of a license or a startup from a UIRC as the dependent variable, with ñno consideration of its impactò (Bozeman, 2000, p. 638).

3.4: Researcher Characteristics

As described in Section 2.4 regarding the structure of Canadian universities and their role and in Canadaôs national innovation system, it has been discussed that university research grants are generally awarded to researchers rather than to universities. With the exception of corporate investments in university infrastructure and large endowments to universities, linkages between universities and firms are generally made at what would be considered in Bozeman et al.ôs (2013) organising framework as the ñcollaboratorò level, rather than the ñorganisationò level. Bozemanôs (2000) Contingent Effectiveness Model of Technology Transfer also describes researchers as important ñtransfer agentsò in the technology transfer process. Therefore, researcher characteristics are particularly important in the Canadian context of this study.

3.4.1: Productivity and Quality

Several studies have investigated the impact of researcher characteristics on technology transfer and commercialisation. Both faculty and students are typically considered researchers (Siegel et al., 2004). However, most studies focus on the characteristics of the faculty members who serve as Principal Investigators (PIs) on research projects. In this study, the PIs are referred to as the ñresearcher(s)ò.

When considering the researcher characteristics that may influence the commercialisation of UIRCs, the academic output they generate and the quality of their output are intuitively good places to start. Owen-Smith and Powell (2001b) argued that publications are the most prolific and the most valued form of academic output. Agrawal and Cockburn (2003) used the number of publications as a measure of research activity to study the impact of ñanchor tenantsò[15] on the absorption of university research by local firms. Van Looy et al. (2004) went one step further by classifying publications based on their discipline (technology or science) and stage (basic or applied).[16] Godin and Gingras (2000) used a similar approach but measured eight disciplines. Both studies found that UIRC does not adversely affect academic productivity. Following Kyvik (1991),

[15] The authors define an anchor tenant as a large, locally present firm that is: (1) heavily engaged in R&D in general and (2) has at least minor absorptive capacity in a particular technological area, which by virtue of its participation in local markets for technology and specialised inputs, may confer significant externalities upon smaller innovative firms.

[16] The study uses the classification system used by the *Science Citation Index* (SCI), developed by CHI Research.

Gulbrandsen and Smeby (2005) developed a productivity index in which all publications were recoded into article equivalents. The study found that researchers involved in a startup company or consulting contract published two more article equivalents than those who were not. However, their model revealed that publishing was not significantly associated with commercialisation outcomes when controlling for other factors.

As a related measure, researcher quality is of central importance to the technology transfer and commercialisation literatures (Di Gregorio and Shane, 2003, Powers, 2003). Godin (1998) was the first to investigate the impact of university researcher quality on collaboration in Canada, and found that high-quality research is a pre-requisite for involvement in multiple collaborative relationships. Godinøs (1998) results are consistent with Blumenthal et al.øs (1996) previous study of life science researchers in the U.S. Perkmann et al. (2013) found that ñthe best and most successful scientists are also those who engage most with industrial partners.ö Ambos et al. (2008) distinguished between the quality of the academic institution and the quality of individual researchers involved in UIRCs. Their study used the number of citations received by a researcherøs publications as a proxy for scientific excellence and found that higher-cited researchers generate more commercial outcomes from UIRCs. Publication quality is also linked to higher impact research, which is itself associated with greater patenting rates (Markman et al., 2008). Lach and Schankerman (2004) used both the number of publications and the number of citations received by the publication as indicators of scientific quality and found that higher quality research leads to higher licensing income.

Several U.S.-based studies have used the faculty quality rating published in the National Research Counciløs (NRC) National Survey of Graduate Faculty (Thursby and

Kemp, 2002, Lach and Schankerman, 2004, Mansfield, 1995, Mansfield and Lee, 1996, Powers, 2003). The survey reports researcher quality at the department level using a five point ordinal scale.[17] Its methodological rigour and comprehensiveness make it a particularly useful tool (Powers, 2003). These studies reported mixed results on the impact of researcher quality using the NRC National Survey of Graduate Faculty. Powers (2003) found the quality of engineering faculty was the only positively significant variable across all three commercialisation outcomes measured in his regression model.[18] However, Thursby and Kemp (2002) found that lower quality researchers had higher technology transfer efficiency, which they attributed to higher quality researchers conducting more basic research.

The researcher productivity and quality measures commonly used in the literature suffer from two limitations that are important for this study. First, data on some proxy measures for productivity and quality can be difficult to collect accurately, leading to potential construct validity problems. Agrawal and Cockburn (2003) and Gulbrandsen and Smeby (2005) both discussed the limitations of publication productivity measures. These authors noted that it can be difficult to appropriately account for multiple authorship in publication data. Agrawal and Cockburn (2003) also discussed their concerns with publication productivity measures because not all research is published or is industrially relevant. With regard to quality measures, there is no equivalent resource in Canada to the U.S.-based NRC National Survey of Graduate Faculty. Ambos et al. (2008) used the *ISI*

[17] The ordinal scale ranges from zero (not sufficient for doctoral education) to five (distinguished).

[18] The study included three dependent variables of technology transfer performance: 1) patents held; 2) licenses executed; and 3) licensing income realised.

Web of Science to count the citations of the researchersô prior publications as a proxy for scientific excellence. The limitations of the *ISI Web of Science* database have been noted in several studies (Leydesdorff, 2008, Meho, 2007, Yang and Meho, 2006). Meho (2007) noted that the *ISI Web of Science* citation database has been criticised by econometricians for indexing a limited number of journals, focused primarily in North America and Western Europe, and for not covering citations of important academic outputs such as books or conference proceedings. Meho (2007) also claimed that the citation database is prone to citing errors such as ñhomographsò, defined as ñfailing to separate citations to two unrelated scientists who happen to share the same last name and first initial.ò Leydesdorff (2008) stated: ñThe assumption that citation and publication practices are homogenous within specialties and fields of science is invalid.ò Yang and Meho (2006) used three different databases to search for citations counts on the same researchers and found the results were considerably different in certain fields of research. Researcher productivity and quality is clearly important, however collecting data for these measures should be approached with caution.

Second, the level of effort and expertise required to collect data on certain measures of researcher productivity and quality are reasonable for academic research purposes, but may not be pragmatic for practitioners in the field, which would be ideal. The absence of an existing reference database on researcher quality in Canada, such as the NRC National Survey of Graduate Faculty, leaves an unfortunate gap. The resources required by research granting agencies like the Ontario Centres of Excellence to collect data and construct productivity and quality measures using data from various databases would outweigh its benefits to the process of selecting the best UIRC projects for funding.

As discussed below, assessing a researcherôs ñembeddednessò in academia may serve as a more practical alternative.

3.4.2: "Embeddedness" in Academia

The concept of embeddedness has been applied in many fields of research, including economics, sociology and anthropology. It was first introduced by Polanyi (1957) to describe how ñeconomic systems, as a rule, are embedded in social relations; distribution of material goods is ensured by noneconomic motives.ò Granovetter (1985) attempted to join economic and social theories of embeddedness, and positioned the concept as economic behaviour embedded within social relationships. This notion raised considerable debate about the role of social networks in economic behaviour. While social theorists argue that social relationships play an important role in economic actions, economic theorists claim that the impact of social relationships is minimal and, in fact, that they create market inefficiencies (Petersen and Rajan, 1994). Regardless of the magnitude of the impact, Uzzi (1996) affirmed that embeddedness as a concept was more useful in explaining some economic actions than economic theories alone, stating that ñembeddedness refers to the process by which social relations shape economic action in ways that some mainstream economic schemes overlook or mis-specifyò. However, Uzzi (1997) cautioned that a theory of embeddedness has yet to emerge, and acknowledged the limitations of embeddedness stemming from the conceptual vagueness about the social mechanisms at play, compared to the specific propositions put forth by economic theories. Despite the contribution of embeddedness to social thought, Block (2003) argued that there remains much confusion around the concept, perhaps best illustrated by Gemiciôs (2008) enumeration of its various interpretations.

Zukin and DiMaggio (1990) identified four forms of embeddedness: structural, cognitive, political and cultural. Ambos et al. (2008) used a form of structural embeddedness to evaluate a university researcherøs ñambidexterityò in their response to the inherent tensions between academic and commercialisation activities. Their study linked a number of individual and organisational characteristics to the likelihood of their UIRCs generating commercial outcomes to better understand how researchers manage both academic and commercial demands. Ambos et al.øs (2008) concept of embeddedness employed the characteristics of the researcherøs academic career, and the ñpath dependencyò induced by their research requirements and the relatively hierarchical structure of universities. They argued that ñacademic faculty are products of their past in the sense that they cultivate certain skills and values and abandon others as the climb career ladders in a particular environmentò. This represents a logical application of the embeddedness concept, since previous studies had shown how the accumulation of social capital by researchers can impact the formation of scientific careers (Bozeman and Corley, 2004).

Ambos et al. (2008) argued that the greater a researcherøs embeddedness in academic research and its hierarchy, the more their skills, relationships and attitude will be geared toward academic outputs rather than commercial outputs. Thus, their study measured embeddedness in two ways: 1) using the researcherøs formal rank (i.e. title), and 2) using the number of years spent by the researcher in academia following the completion of their PhD. They justify this operationalisation of embeddedness by suggesting that researchers with a higher rank should have greater experience, more expertise and a better reputation than more junior researchers, thereby ñlockingò them more deeply into traditional academic culture. This approach to embeddedness is therefore closely tied to researcher productivity and quality, which are also associated with experience, expertise and reputation (Gulbrandsen and Smeby, 2005). Ambos et al. (2008) make the further claim that younger researchers have been trained to consider the industrial relevance of their research and may be more accustomed to raising industry funding for their research. Finally, Ambos et al. (2008) remarked that more commercially-oriented researchers tend to leave academia to pursue industrial research (Dietz and Bozeman, 2005), further concentrating the remaining proportion of academically-minded researchers over time.

As described previously, Ambos et al.ôs (2008) model found a strong negative association between embeddedness and commercial outcomes from UIRCs. Their study also found that a researcherôs scientific excellence (measured by publication citations) was positively associated with commercialisation. The younger, less-senior and higher-cited researchers found by Ambos et al. (2008) to produce the most commercial outcomes were likened to the category of ñstar scientistsò identified by Zucker and Darby (2001), ñwho by virtue of their all-round excellence are able to rise above the normative boundaries that constrain the behaviour of other facultyò (Ambos et al., 2008).

Other studies have attempted to categorise researchers in related ways. Owen-Smith and Powell (2001a) found that a dichotomous split between ñold-schoolò researchers who believe academia and industry should be separate, and ñnew-schoolò researchers who embraced convergence between academia and industry, was not sufficient to capture the variation in researcher views on commercialisation of life sciences research. They added two hybrid categories of researchers: ñreluctant entrepreneursò, and ñengaged traditionalistsò. Dietz and Bozeman (2005) divided researchers with ñdiverseò career patterns including industry experience, from those with ñhomogenousò career patterns rooted primarily in academia. They found that a higher proportion of a researcher’s career spent in industry was negatively associated with publication productivity but positively associated with patent productivity. Lam (2005) identified a growing category of “linked scientists” with overlapping knowledge networks between academia and industry. She identified three sub-categories of linked scientists with different roles in researcher and firm engagement: 1) entrepreneurial professors at universities; 2) joint appointments formally affiliated with universities but appointed to collaborative projects; and, 3) post-doctoral fellows selected by firms.

Several empirical studies in the university technology transfer literature have used variables related to Ambos et al.’s concept of embeddedness. Perkmann’s (2013) review of the literature on university-industry relations cited numerous studies that have found a positive relationship between a researcher’s seniority and their propensity to engage in UIRCs (Boardman, 2008, 2009, Boardman and Corley, 2008, Ponomariov and Craig Boardman, 2008, Bozeman and Gaughan, 2007, D’este and Perkmann, 2011, Haeussler and Colyvas, 2011, Link et al., 2007). Lee (2000) categorised faculty members based on their titles and found that full professors are more likely to disclose inventions and to patent. Alternatively, Azagra-Caro et al. (2006) created a novel measure of researcher seniority but found no evidence that seniority leads to greater support for the objectives of UIRC.[19] Ponomariov and Boardman (2010) found no significant relationship between a researcher’s seniority and their publishing record in collaboration with industry, controlling for other factors.

[19] The study considered a researcher to have seniority if the following conditions were met: 1) the professor is older than forty years; 2) his/her teaching experience has lasted at least ten years; 3) his/her teaching scale is the highest (full professor); and 4) he/she has received at least one Spanish 6-year term research award.

According to Bozeman et al. (2013), ñrelatively few studies have examined the effects of age and career age on collaboration.ò Perkmann et al. (2013) found that the role of age in commercialisation was ambiguous. Some studies have suggested that younger researchers may be more predisposed to commercialisation because it has more recently become a legitimised practice in academia (Bercovitz and Feldman, 2008). Lach and Schankerman (2004) found that untenured researchers were less responsive to different university royalty sharing policies at public universities.

The concept of embeddedness has been applied in many contexts to explain how social networks affect economic behaviour. A novel operationalisation of structural embeddedness was used by Ambos et al. (2008) to better understand how a researcherôs career position affects their academic and commercial outputs. Other studies in the university research and university technology transfer literature have explored related concepts. Embeddedness is a relatively simple and useful measure to apply in practice, and may capture at least part of the effect of researcher productivity and quality, since it is reasonable to assume that more productive and higher quality researchers would become more embedded in academia over time.

3.5: Firm Characteristics

Beginning with Arrow (1962), numerous empirical studies have demonstrated the positive impact of research and development on growth and productivity at the firm, industry and national level. As described in Chapter II, governments in Canada and other countries, such as the U.S. and the U.K., provide significant direct and indirect support for firm research and development, offering ñtestimony to the importance of Nelsonôs (1959) and Arrowôs (1962) early insights into the motives underlying R&D investmentsò (Becker, 2015). In essence, the argument in favour of public support for private research is that the private rate of return on research investments is lower than the social rate of return, leading firms to under-invest in research (Arrow, 1962, Griliches, 1979). The ópublic goodô portion of the research would prevent firms from appropriating all the potential benefits from the outcomes. Other firms would have the opportunity to ñfree rideò on the spillover benefits of the research. ñPolicymakers could then contribute to reducing the cost of riskier but socially valuable R&D projects, increasing the firmsô expected return to such R&D projectsò (Zúñiga-Vicente et al., 2014). Governments, provide direct support for collaboration between firms and other organisations as a mechanism for the generation of ideas and knowledge transfer in national innovation systems.

For firms, research collaboration can be an important way to mitigate risk, reduce the cost of conducting research, and gain access to skills and expertise. Gulati (1998) defined collaboration as ña voluntary arrangement in which two organisations engage in a mutually beneficial exchangeò (Galán-Muros and Plewa, 2016). Canadaôs support for university-industry research collaboration (UIRC) is particularly strong, ranking first among the G7 countries (Hanel and St-Pierre, 2006). Important Canadian UIRC support programs like the national Networks of Centres of Excellence (NCE) or the provincial Ontario Centres of Excellence (OCE), consider the level of firm contribution to UIRCs as part of their funding evaluation criteria.

3.5.1: Firm Contributions to UIRC

From the perspective of university researchers, Kesting et al. (2014) acknowledged the growing importance of third-party funding in maintaining their research agenda and other activities. In the face of shrinking public funding for research in jurisdictions like

Europe, or in the overall goal of increasing their research budgets, researchers face increasing pressure from universities to cultivate private sector relationships and to raise funding from firms to support their research (Perkmann et al., 2013). These developments are in line with Leeôs (1996) utility maximisation theory, which ñlinks institutional behaviour to the need for research dollarsò.

Later, Lee (1998) speculated that increased researcher involvement in commercialisation activity in the U.S. provided incentives for researchers to raise research funding from industry in order to further their career (Perkmann et al., 2013). Kesting found that a researcherôs propensity to acquire research funding from firms depended primarily on their attitude towards UIRC and their ñresearch focus and agendaò. Their study found no significant relationship between a researcherôs ñdegree of obligationò to acquire external research funding and their propensity to engage in UIRC. Pressure for researchers to raise industry funding may be higher within systems like Canada, the U.S. and the U.K., where access to both firm and government funding is highly competitive. Conversely, the pressure may be lower within universities where researchers receive endowments or discretionary research funds (Haeussler and Colyvas, 2011).

From the firm perspective, UIRCs help to reduce the risk involved in research activity by sharing skills and expertise, and by sharing costs (Muscio et al., 2014). Financial constraints within the firm can make research collaboration a more attractive option. A number of empirical studies have concluded that cost sharing is an important consideration in a firmôs decision to enter into a UIRC (Becker, 2015, Abramovsky et al., 2009). However, these same financial constraints can also make it challenging for firms to provide adequate funding for UIRC (Howells et al., 2012). Notwithstanding the risks and resource constraints, Landry et al. (2007a) argued that Canadian firms have a social responsibility to fund university research in their examination of the determinants of knowledge transfer in the fields of natural sciences and engineering.

Firms that engage in university research funding often do so on a competitive basis, using processes of varying levels of formality to identify the collaborations that best meet their objectives. Connolly (1997) suggested that firms aim to allocate funding to the researchers and universities of the highest possible quality. Therefore, the level of research funding of universities or the level of funding allocated by firms to UIRCs provides some information about quality (Muscio et al., 2013).

Some empirical studies have investigated the relationship between firm contributions to research and commercialisation. As previously discussed, Ambos et al. (2008) used a firmős contribution as the only firm-related characteristic in their study of commercial outcomes from UIRCs. Their study used a binary variable to measure whether a cash contribution was made by the firm to the UIRC, and found no significant relationship between firm contribution and commercial outcome.

Gulbrandsen and Smeby (2005) claimed to be the first to examine the link between industry funding and commercialisation specifically. They found that researchers who received industry funding were more likely to generate commercial output. Their model estimated that the probability of conducting R&D that would lead to a startup company increased from two to eight percent if a professor received industrial funding. The probability increased to 18 percent if the professor also collaborated with industry colleagues and to 30 percent if the research was in a technology field. Gulbrandsen and

Smebyôs (2005) results confirm those of earlier studies (Godin, 1998, Van Looy et al., 2004) which found that researchers with industry funding are more productive.[20] However, Geuna and Nesta (2006) cautioned that the directionality of the relationship between industry funding and commercialisation in Gulbrandsen and Smebyôs (2005) study remains unclear. Lawsonôs (2013) study of researchers in the U.K. found that researchers who received a higher proportion of their research funding from industry had a higher likelihood of patenting. Similarly, Hottentrottôs (2011) study of researchers in Germany found that higher research funding from firms was positively associated with patent citations.

3.5.2: Crowding-In vs. Crowding-Out

As described in Chapter II, governments in Canada, the U.S., the U.K., and in other OECD countries provide financial incentives for UIRC in order to maximise the economic and social returns from investments in research (Abramovsky et al., 2009). With pressure from universities and government granting agencies, researchers increasingly rely on industry funding to bolster their research budgets. Among other reasons, firms engage in UIRC as a means of reducing the risk and the cost of research, but resource constraints often serve as a barrier to collaboration.

In this context, government subsidies supporting UIRC may increase, or ñcrowd-inò, firm research spending by creating financial incentives for collaboration. The concept of crowding-in suggests that government funding for research will have a ñcomplementaryò effect on industry research funding. The concept is also referred to as ñadditionalityò, and defined as ñthe extent to which public support stimulates new R&D activity as opposed to

[20] Godin measured sixteen outputs of researcher productivity, while Van Looy measured only publications.

subsidizing what would have taken place anyway (Buisseret et al., 1995). Conversely, ñcrowding-outò is the concept that government funding for research ñsubstitutesò private sector research that would have otherwise taken place anyway.

Crowding-in/out is a concept widely used in economics to explain the effect of government involvement in a sector of the market economy (Spencer and Yohe, 1970). Blank and Stigler (1957) were the first to explore the effect of publicly-funded research on private research investment. Their study found mixed results for both crowding-in and crowding-out effects, which is emblematic of the diverse results reported on similar work since then (Zúñiga-Vicente et al., 2014).

Czarnitzki et al. (2007) noted: ñEconomic theory has no clear prediction on the effects of cooperative research on R&D expenditure. If spill-over effects are low, firms would reduce R&D. In contrast, sufficiently high spill-over effects would lead to increased R&D expenditure. However, the risk of free riding on partnersô R&D activities may countervail the positive effects due to spill-overs.ò Indeed, the literature is split on whether government subsidies crowd-in or crowd-out private sector research.

Garcia-Quevedo (2004) provided an excellent summary of the econometric evidence in the literature supporting crowding-in or crowding-out of research activity.

Table 3.1: Summary of Econometric Evidence for Crowding-In/Out

	Complementarity	Insignificant	Substitutability	Total
By level of analysis:				
Firm	17	10	11	**38**
Industry	8	3	1	**12**
Country	13	6	5	**24**
Total	**38**	**19**	**17**	**74**
By jurisdiction:				
U.S.	22	13	10	**45**
Non U.S.	16	6	7	**29**
Total	**38**	**19**	**17**	**74**

Source: Adapted from Garcia-Quevedo (2004)

Garcia-Quevedoõs (2004) analysis showed that 51.4 percent of the empirical evidence in the literature supported complementarity, while 23 percent supported substitutability. Beckerõs (2015) more recent survey of the literature found that ñthe large body of more recent literature observes a shift away from the earlier findings that public subsidies often crowd-out private R&D to finding that subsidies typically stimulate private R&D.ò

For example, Hanel and St-Pierreõs (2006) study of Canadian manufacturing firms noted frequent collaboration with universities in knowledge-based industries, and found that ñresearch undertaken in partnerships complements, rather than replaces, R&D by collaborating firms.ò Abramovski (2009) studied firms in Germany, France and Spain, and found that firms who reported financial constraints in their research budgets were more likely to be involved in a UIRC. Abramovskiõs (2009) results were similar, and followed the same methodology, as Cassiman et al. (2002). Czarnitzki et al.õs (2007) study of Finnish and German firms found that subsidies for UIRC would result in increased firm research spending. In the U.S., Jensen et al.õs (2010) study of researchers at eight major research universities found complementarity between government and firm funding for university research. Bloom-Kohute et al.ôs (2009) study of nearly ten years of U.S. federal research funding in life sciences found that increased federal funding for university research was positively associated with increased non-federal funding. Becker (2015) aptly summarised his survey of the literature as follows: ñTaken together, the results from this strand of the literature suggest that governments may increase private R&D spending by facilitating and incentivising R&D cooperation.ò

3.5.3: Amount and Type of Firm Contribution

The level of government subsidy and the amount of firm contribution to a UIRC can vary significantly between projects, and may be an important antecedent for the projectôs success. Relatively few studies have assessed the effect of the relative size of the government subsidy and firm contribution to a research project, despite the large body of literature on government crowding-in/out (Zúñiga-Vicente et al., 2014). Aschhoff (2009) found that larger research projects in Germany may be more dependent on government subsidies, and that a minimum size of subsidy was required to create additionality in firm research activities. Therefore, for a given subsidy amount, there was a greater chance of crowding-in for larger projects. Guellec and Pottelsberghe (2003) studied the level of government research funding in 17 OECD countries. They found that the stimulating effect of subsidies increased to a certain threshold, then decreased beyond it. Both Zhu et al.ô (2006) study of direct research subsidy programs in Shanghai, and Gorg and Stroblôs (2007) study of domestic manufacturing firms in Ireland, suggested a crowding-in effect to a certain level. Interestingly, Gorg and Strobl (2007) found no evidence of additionality or substitutability in the research expenditures of foreign-owned manufacturers in Ireland, regardless of the size of the government subsidy.

In practice, there are three reasons why government granting agencies that support UIRC seek higher firm contributions to projects. First, higher firm contributions embody the agencyøs goal of maximising private research activity. The greater the firm contribution, the greater the additionality of the subsidy provided by the granting agency. Second, assuming that a UIRCøs budget is fixed, a higher proportion of firm contribution to the project budget means a lower subsidy is required. This makes more efficient use of limited government resources, and allows granting agencies to fund more UIRC projects. Lastly, and perhaps most importantly from the granting agencyøs perspective, larger firm contributions may demonstrate a stronger interest by the firm in the research, and in the commercialisation of its results. As described above, several studies have found a positive association between industry funding of university research and commercialisation at an aggregate level (Lawson, 2013, Hottenrott and Thorwarth, 2011, Gulbrandsen and Smeby, 2005). However, no project-level studies were found that linked firm contributions to a UIRC with its commercial outcomes.

It should also be noted that not all types of firm contributions may be considered equally by government granting agencies that support UIRCs. ñCashò contributions represent direct monetary support toward the budget and research activities of the UIRC. ñIn-kindò contributions represent indirect support of the UIRCøs research activities, such as staff time, and access to equipment or facilities. Cash contributions are often preferred by granting agencies because they are tangible. ñCash is kingò, said a Business Development Manager at the Ontario Centres of Excellence when discussing her views on the perceived difference between cash and in-kind contributions from firms. However, as described above in Bozemanôs (2000) Contingent Effectiveness Model of Technology Transfer, there are many reasons why firms may engage in collaboration, let alone contribute cash to UIRCs, such as philanthropy or public relations, which are not tied to a firmôs research interests or commercial intent. In-kind contributions may be viewed with skepticism by granting agencies because they are considered ñsoftò. Indeed, the value of in-kind contributions can be difficult to calculate and hence are prone to exaggeration or overstatement. However, in-kind contributions may also help capture the effect of informal networks and relationships, especially in the case of in-kind contributions of staff time, on the projectôs commercial outcomes (Galán-Muros and Plewa, 2016). Ambos et al. (2008) included a dummy variable to capture the presence of firm cash contributions to UIRCs funded by a U.K. research council. Their study found no significant relationship between a firmôs cash contribution and the UIRCs commercial outcomes. The fact that Ambos et al. (2008) only measured the presence of a firm cash contribution to the UIRC, and not the magnitude of the firmôs contribution, was an important limitation of their study.

The measurement of firm contributions to UIRCs has a number of limitations. First, funding for university research by firms does not necessarily imply collaboration, and vice versa. Approximately one third of researchers in Gulbrandsen and Smebyôs (2005) study who had industry funding had no regular collaboration with industry colleagues. Conversely, approximately one third of researchers who collaborated regularly with industry colleagues had no industry funding. Second, industry funding does not necessarily imply quality of research. Well-known researchers tend to attract more resources, which is not always due to the researcherôs ñreal innate abilitiesò (Geuna, 2001, p. 625).

Research is important to firm productivity and competitiveness; therefore governments provide public support for private research in order to improve productivity and competitiveness at a national level. University-industry research collaboration (UIRC) is an increasingly important mechanism of collaboration and technology transfer supported by governments. University researchers receive institutional pressure to increase their research budget by raising industry funding. Firms seek to de-risk their research by cost sharing with universities and government granting agencies. There is mounting evidence that government subsidies for research collaboration help to stimulate greater private sector research. The level of government subsidy or firm contribution to a UIRC may influence its commercial outcomes. However, cash or in-kind contributions may produce different effects.

3.6: Project Characteristics

As described in Chapter II, Canadaõs private sector research intensity is significantly lower than that of other OECD countries, such as the U.S. and the U.K. In addition, the research performance of Canadian firms varies significantly by industry. For example, in 2005, the research intensity of the Canadian office and computer equipment industry was 71.5 times greater than that of the automotive sector (see Section 2.3). Such industry differences are unique to Canada and are due in part to three main factors; Canadaõs geographic proximity to the U.S., the high level of integration of the Canadian and U.S. economies, and the high level of foreign ownership of Canadian firms. Various levels of government in Canada have developed sector-based initiatives, such as the federal Networks of Centres of Excellence (NCE) and provincial Ontario Centres of Excellence, to encourage research collaboration and increase the research intensity within industries of strategic importance. Therefore, understanding how sector differences influence the commercialisation of UIRC outcomes is particularly important in the Canadian context of this study.

3.6.1: Absorptive Capacity

A robust body of academic literature has found evidence that firms which invest greater resources in research have an increased capacity to absorb knowledge from their external environment, including from universities. The theory of absorptive capacity explains how firms recognise new, valuable, and relevant knowledge, assimilate it into their processes, and apply it commercially (Bierly et al., 2009). Cohen and Levinthal (1990) were the first to suggest that ñabsorptive capacity may be created as a byproduct of a firm's R&D investment.ò Their seminal study found that research intensity increased a firmÕs absorptive capacity, and explained why some firms invest in research even when much of the benefits spill over into the public domain (Cohen and Levinthal, 1990). Absorptive capacity creates a sustainable competitive advantage for firms, and due to the knowledge spillovers that research generates, contributes to the competitive advantage of industries as a whole.

Several studies have investigated the relationship between absorptive capacity and industry engagement with universities. Arundel and Geuna (2004) and Bierly et al. (2009) used the ratio of R&D expenditures to sales as a proxy for a firmÕs absorptive capacity. Bierly et al. (2009) found that greater absorptive capacity helps firms assimilate tacit knowledge from research collaborations with universities. Geuna (2004) found that the importance of proximity for sourcing knowledge from public research is lower when a firmÕs absorptive capacity is higher. Fontana et al. (2006) used the ratio of R&D

employment to total employment as a proxy for absorptive capacity, and found it positively associated with a firmös likelihood of collaboration with universities.

Knockaertös et al.ös (2014) study of nine research centres in Belgium found that firms with greater absorptive capacity were more likely to benefit from research subsidies and the assistance of intermediary organisations. Tether and Tajar (2008) studied firm engagement with specialist knowledge providers in the U.K., including universities. Their study found that firms with higher absorptive capacity had a greater likelihood to engage with universities. In contrast to studies in the U.S. and other strong knowledge-based economies, Azagra-Caro (2006) found that faculty did not respond to greater encouragement from the university to engage in UIRC in a region with low absorptive capacity. It would appear that absorptive capacity at a regional, national or industry level can influence firm engagement with universities.

3.6.2: Industry Differences

Firms with greater absorptive capacity are better able to assimilate and exploit external knowledge. A key measure of absorptive capacity is research intensity, which can differ considerably between firms, regions and industries. Therefore, it is reasonable to expect that firms in certain industry sectors may be more likely to engage with universities than others (Bramwell et al., 2012). Perkmann et al.ös (2013) review of the literature on academic engagement with industry cited numerous studies that found sector-specific patterns of university-industry collaboration. For example, Grossman et al. (2001) stated: ñEach of the industry sectors provides a distinctive environment and set of somewhat different challenges for university researchers. As a result, the nature of the university-industry research interaction varies from sector to sector.ò Their study found considerable differences in university-industry engagement in certain U.S. industries. The medical and ICT sectors have developed very strong linkages to universities, to the extent of causing concern over the ability of universities to adapt and respond to the growing needs of these industries. However, the culture gap between industry and academic researchers in the transportation and financial services sectors is cited as the reason for relatively little collaboration (Grossman et al., 2001).

In a more recent example, Geigerôs (2012) examination of university-industry interaction in four industry sectors in the U.S. found patterns of engagement that are similar to those found in some Canadian industries; significant university engagement by the pharmaceutical sector involving highly formalised collaborations, and relatively low levels of informal university engagement in the manufacturing sector. Interestingly, their study also found low levels of university interaction in the U.S. ICT, in contrast to both Grossman et al.ôs (2001) earlier findings and the relatively high levels of university interaction found in the Canadian ICT sector (see Section 2.6). However, Geiger (2012) noted that this is due primarily to the high level of competition and the frenetic pace of technological development in the ICT sector, rather than low absorptive capacity.

Some studies have found considerable differences in university commercialisation performance among various industry sectors. Landry et al. (2007b) examined sectoral differences in the commercialisation activity of Canadian university researchers in engineering and life-sciences. They found that ñresearchers in engineering are significantly more involved in knowledge transfer than their colleagues in other research fieldsò (Landry et al., 2007b). In an earlier study focused specifically on startup activity at Canadian universities, Landry et al. (2006) found that Canadian sectors with high absorptive capacity, such as computer sciences and engineering, had the highest proportion of researchers who had created a startup (25.4% and 22.8% of researchers, respectively) compared to other fields of natural science. Ambos et al.ôs (2008) study of UIRCs in engineering and physical sciences in the U.K. used a control variable for each science field but found no significant relationship with commercial outcomes. Gulbrandsen and Smeby (2005) categorised Norwegian researchers into five academic fields, according to the guidelines suggested by UNSECO.[21] Their study found that researchers in technology-based fields who received industry funding were considerably more likely to create a startup.

Mowery et al. (2015) found that the pharmaceutical and electronics sectors, both of which have high research intensity in Canada and the U.S., ñstand out among industries that view university research results as importantò. Indeed, the biotechnology industry is responsible for 50 percent of all university patents, licenses, royalty income and startup companies in Canada and the United States (Mowery and Nelson, 2001). Thursby and Kemp (2002) used three academic fields and found that biological sciences and engineering were more important to licensing activity than physical sciences due to their more applied nature and the larger market for those technologies. Several studies have found that applied fields of research, such as engineering, improve the likelihood of engagement in UIRC and commercialisation compared to natural or social sciences (Bekkers and Bodas Freitas, 2008, Boardman, 2008, 2009, Bozeman and Gaughan, 2007, Ponomariov, 2008).

[21] The five academic fields were: 1) natural sciences; 2) social sciences; 3) technological disciplines,;4) the humanities; and 5) medicine. The categorisation is based on the *UNESCO Recommendation Concerning the International Standardization of Statistics on Science and Technology*, 1978.

The theory of absorptive capacity describes the impact of research intensity on a firmôs ability to identify, assimilate and exploit external knowledge. As previously discussed, the research intensity of Canadian firms is low compared to other industrialised countries. However, Canadaôs research intensity in certain key knowledge-based industries is on par or higher than that of the U.S. As predicted by the theory of absorptive capacity, different industries adopt unique patterns of engagement with universities in research and commercialisation activities. Several studies in Canada, the U.S. and Europe have found evidence that industry sectors with higher research intensity tend to engage more with universities, and that university commercialisation performance is greater in sectors with high absorptive capacity.

3.7: Other Empirical Studies

The previous three sections have described the theoretical foundation for the relationship between embeddedness, crowding-in/out, and absorptive capacity and the commercialisation of UIRC outcomes. There is empirical evidence in the extant literature that a number of other factors may influence university-industry interaction and university technology transfer performance. The most relevant among these additional factors are described below, along with a discussion of common research methodology found in the related literature.

3.7.1: Additional Researcher Characteristics

Demographics: The impact of researcher demographics, such as gender and age, has been examined in several studies. Studies on the effects of gender and age on research productivity report mixed results and are only relevant insofar as research productivity affects commercialisation. Many studies identify a ñgender gapò in the research productivity of women and men. For example, Stack (2004) found than men publish significantly more than women in U.S. universities. However, Xie and Shauman (1998) found that this gap narrows significantly when controlling for sufficient personal, structural, and resource variables. Two studies by Stephan (Stephan, 1996, Levin and Stephan, 1991) conclude that age has a weak inverse relation to research productivity and the acceptance of new ideas.

Some studies explore the relationship between gender, research collaboration and commercialisation. In a study of physical and engineering scientists in the UK, Tartari and Salter (2015) found that female researchers engaged less with industry and in different ways than comparable male counterparts. However, they also found that these differences could be mitigated by moderating the social context of the engagement. Gulbrandsen and Smeby (2005) used gender and age as independent variables and found that each has only a ñlimited and weak relationò (Gulbrandsen and Smeby, 2005, p. 944) to commercialisation. More recently, Bozeman and Gaughan (2011) found that men and women have relatively few differences with regard to research collaborations. In fact, the study found that women have more collaborators, after controlling for various other factors.

Previous Interaction with Firms: Several studies have explored the relationship between a researcherôs previous engagement with firms and future commercialisation outcomes. Following Gulbrandsen and Smeby (2005), Ambos et al. (2008) surmised that ñresearchers with experience in industry interactions may be in a better position to produce commercial outputsò. They measured industry interaction by counting the number of previous grants received by the researcher from the funding agency that provided the data for the study.

Ultimately, Ambos et al. (2008) found that the researcherõs level of interaction with industry was not significantly associated with commercial outcomes from UIRCs.

A number of studies have examined the impact of the researcherõs previous interaction with firms through UIRCs on the propensity to undertake future collaborations and on the likelihood of becoming involved in commercialisation. ñFrequent and recurrent partners are particularly likely to capitalise on their collaboration experience by transferring the information and knowledge gained through their involvement in multiple and diverse partnerships.ò (Bruneel et al., 2010) Participation in UIRCs has been positively associated with commercialisation, including patenting and startup creation (Bekkers and Bodas Freitas, 2008). In addition, Hertzfeld et al. (2006) found that prior experience in UIRCs made future collaborative agreement easier to set up and facilitated the negotiation of commercial terms for technology transfer.

3.7.2: Additional Firm Characteristics

Number of Firms: UIRCs may involve multiple industry collaborators. Lee (2000) found that 65 percent of UIRCs are funded by single firms, 28 percent by small consortia of two to ten firms, five percent by medium consortia of 11 to 25 firms, and two percent by large consortia of 26 to 94 firms. Many firms prefer not to undertake UIRCs involving other firms for fear of technology leakage or loss of competitive advantage (Barnes et al., 2006, Newberg and Dunn, 2002). However, Perkmann and Salter (2012) cite a number of advantages for firms who chose to collaborate with universities in consortia, including greater leveraging of funds from public or third-party sources.

Previous Interaction with Universities: Relatively few studies have explored the impact of the firmøs previous interaction with university researchers through UIRCs on their propensity to engage in future collaborations or commercialisation. Min and Kim (2014) found that ña firmøs external knowledge acquisition through previous R&D partnership with [public research institutes and universities] fortifies the positive effects of potential absorptive capacity on the commercial success of technology transferred from [public research institutes and universities].ö Mora-Valentin et al.øs (2004) study on the determining factors in the success of R&D collaborations between firms and research organisations found that previous UIRC experience had a positive influence on the success of future UIRCs.

With regard to measuring a researcherøs previous interaction with industry, Bierly et al. (2009) used a three-item scale, following a similar measure used by the Industrial Research Institute[22]. Mora-Valentin et al. (2004) also cited that interaction has been measured in a number of Spanish studies by using prior linkages, common prior business dealings or previous collaborations on specific projects (Rialp-Criado, 1999, García-Canal and Valdés Llaneza, 2000, Reuer and Ariño, 2002).

Firm Size: Fontana et al. (2006) stated that ñthe role of firm size in influencing the propensity of firms to collaborate with [public research organisations] is one of the basic tenets of the literature on universityï industry relationships as acknowledged in recent empirical investigations (Mohnen and Hoareau, 2003, Cohen et al., 2002, Arundel and

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[22] Whereas the Industrial Research Instituteøs measure concerned a firmøs general experience with UIRC, Bierly et al.øs (2006) measure included more specific experience related to a firmøs application of external knowledge from UIRCs to R&D, production, and information-technology activities.

Geuna, 2004, Laursen and Salter, 2004).ò Several studies have used the number of employees as a measure of firm size (Santoro and Gopalakrishnan, 2001, Cohen et al., 2002) rather than sales because it is more relevant to the likelihood establishing relationships with universities (Mohnen and Hoareau, 2003). Laursen and Salter (2004) used both firm size and whether or not a firm is a startup as variables to measure the likelihood to collaborate. Fontana et al. (2006) used both the total number of employees and the number of R&D employees as ñabsoluteò and ñrelativeò measures of size. These studies found that larger companies, and to a much lesser extent startups, have a greater likelihood to collaborate with universities and are more involved in commercialisation.

Results are mixed on whether the greater likelihood to collaborate among large firms corresponds to an increased capacity to commercialise project outcomes. Schartinger et al. (2001) drew a link between firm size and absorptive capacity, pointing to the robust empirical evidence that R&D increases with firm size. However, Jaffeôs (1989) knowledge production function suggests that smaller companies have a ñcomparative advantage at exploiting spillovers from university laboratoriesò (Acs et al., 1994, p. 340). Cohen and Klepper (1996) found that lower R&D productivity by larger firms is due to ñcost spreadingò, or the effect of averaging the benefits of R&D over higher fixed costs. More recently, Grimpe and Hussinger (2013) found that firms engaged in university technology transfer tended to be larger in terms of key measures such as total number of employees, highly skilled employees, R&D intensity, and innovation sales as a percentage of total sales. Grimpe and Hussinger (2013) stated that ñfirm size and absorptive capacity as is reflected by R&D intensity are important to engage in any technology transfer from the university.ò

3.7.3: Additional University Characteristics

Technology Transfer Offices: Several managerial and organisational characteristics have been investigated to explain the variance in technology transfer performance between universities (Siegel et al., 2004). The systems, structure, staffing and productivity of university Technology Transfer Offices (TTOs) are important factors in successful technology transfer (Rothaermel et al., 2007). TTOs can be structured internally (part of the university administration) or externally (an independent organisation reporting to the university administration). Ambos et al. (2008) included several measures related to the universityôs TTO, as well as the universityôs scientific excellence in their study of commercial outcomes from UIRCs. Interestingly, their study found that the mere presence of a TTO at the university was significantly associated with commercial outcomes from UIRCs. However, specific measures related to the TTO, including breadth of TTO support and experience of the TTO, were not significant. Ambos et al. (2008) hypothesised that breadth of support and experience may instead be more relevant at later stages of commercialisation. Gonzalez-Pernia et al.ôs (2013) assessment of the determinants of university technology transfer found that the number of TTO professional staff and the TTOôs experience, measured by TTOôs years in operation, were positively and significantly associated with startups.

TTO productivity is typically investigated in relation to invention disclosures. Controlling for other factors, a number of studies have found a positive relationship between the number of inventions disclosed and commercialisation (Siegel et al., 2008, Chapple et al., 2005, Friedman and Silberman, 2003, Thursby and Kemp, 2002, Thursby et al., 2001). Dolmans et al. (2016) found that TTO staffôs perception of a researcher can influence their judgement of whether an invention is more appropriate for a license or a startup. Conversely, researchersô perception of the TTO can influence their likelihood to disclose quality inventions (Ismail et al., 2015, Jensen et al., 2003).

Feldman et al. (2002) found that greater financial independence of TTOs from the university administration promotes equity over royalties in licensing agreements. Bercovitz et al.ôs (2001) smaller case study of three dissimilar U.S. university TTOs found similar results. Siegel et al.ôs (2004) study of U.S. technology transfer staff concluded that dedicating more resources to technology transfer generates more patents and licenses. However, the study did not acknowledge the potential bias of technology transfer staff, who may have cited lack of resources as a rationalisation for weak technology transfer performance, and who would benefit directly from additional resources. Powers (2003) found that TTO staff size positively affected the number of licenses and licensing income. Other studies have emphasised the importance of having the right business development skills (Lockett and Wright, 2005, Siegel et al., 2003, O'Shea et al., 2005) in addition to sufficient resources.

González-Pernía et al. (2013) found that a TTOôs experience is positively and significantly associated with the number of licensing agreements signed in a given year. Powers (2003) also found that TTO age positively affects the number of patents and licenses. However, two separate studies by Siegel (Siegel et al., 2003, Siegel et al., 2008) provided contradictory evidence on the subject.[23]

[23] Siegel et al.ôs (2003) stochastic frontier estimation (SFE) model found that older TTOs are closer to the frontier, pointing to greater efficiency and a learning effect over time. Siegel et al.ôs (2008) SFE modeling of

IP Ownership: As described in Section 2.6 of the preceding chapter, there is a significant difference between the intellectual property (IP) ownership policies of universities in Canada and those in the United States and the United Kingdom. U.S. based technology transfer is the subject of most literature involving university IP policies, where the Bayh-Dole Act of 1980[24] has created a national technology transfer framework. In Canada, each university has adopted unique technology transfer policies (Statistics Canada, 2008), which can affect the relative technology performance of universities.

The universityợs IP policy, which typically defines both IP ownership and the distribution of royalty revenue, is an important characteristic. Lach and Schankerman (2004) presented econometric evidence that universities which distribute a higher share of royalties to academic researchers generate higher licensing income. The study found that incentive effects decline with university quality and increase the quality rather than the quantity of inventions. However, Siegel et al.ợs (2004) study of five mid-tier U.S. universities concluded that greater rewards for faculty involvement in commercialisation generates more patents and licenses, suggesting an increase in the quantity of commercial outcomes. Azagra-Caro et al. (2006) found that higher incentives had no effect on faculty support for the objectives of UIRC. More research is needed on the impact of pecuniary and non-pecuniary incentives on university technology transfer (Markman et al., 2008).

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technology transfer performance in the U.S. and the United Kingdom (U.K.) found that older TTOs are less efficient, contrary to the studyợs proposition.

[24] The Bayhï Dole Act (P.L. 96-517, Patent and Trademark Act Amendments of 1980) created a uniform IP policy among U.S. federal research funding agencies that enabled organisations who receive federal research funding to retain title to their inventions. The Bayh-Dole Act was considered instrumental in encouraging universities to participate in technology transfer activities.

University IP policies can be challenging to use in longitudinal research studies because of the potential for policies to change over time. However, Lack and Schankerman (2004) found that seventy percent of respondent universities in their study had not changed their royalty distribution policy between 1991 and 1999.

University Size: The size and scope of the universityôs resources can impact commercialisation (Wright et al., 2004). Algieri et al. (2013) stated that ñthe greater the skills, and the number of scientists within a university, and the higher the funding - which includes government support mechanisms and policy initiatives to develop venture capital - the greater the growth potential of new startups.ò Lach and Schankerman (2004) measured the number of faculty members in doctoral programs, since departments without Ph.D. programs contribute less to commercial outcomes (Thursby and Kemp, 2002). Siegel et al. (2008) and Mowery and Nelson (2001) studied the link between technology transfer efficiency and the presence of a medical school on campus, suggesting that medical inventions are more marketable than those from other disciplines (Powers, 2003). However, both Siegel et al. (2008) and Powers (2003) found that the presence of a medical school did not affect growth in licensing activity.

Previous studies have classified universities based on the size of institutional research expenditures (Lee, 1996, Azagra-Caro et al., 2006). Lee (1996) found that mid to low tier universities provide a more collaborative climate, possibly because prestigious universities with larger R&D budgets are more focused on basic research (Mansfield, 1995). OôShea (2005) and Powers (2003) used the amount of federal funding in science and engineering to classify universities. The level of federal funding was positively associated with startup activity in OôSheaôs (2005) study and patenting activity in Powersô (2003) study, but that relationship disappeared when considering licensing income. Powers (2003) attributed this to the weighting of federal funding towards basic research.

Reputation: Sine et al. (2003) found that institutional prestige[25] had a positive effect on licensing, controlling for several factors including presence of a medical school, regional research activity and TTO resources. This creates what the study called a ñhaloò effect in commercialisation activity, similar to the Matthew effect with university publications (Merton, 1968).

3.7.4: Additional Project Characteristics

Proximity: It is intuitive that the geographic distance between the stakeholders in a UIRC, particularly between the researcher and the firm, should affect the outcomes of the collaboration. Indeed, D'Este et al. (2012) stated: ñour results, not surprisingly, show that geographical proximity makes [university-industry] research partnerships more likely.ò Agrawal and Cockburn (2003) argued that successful technology transfer also requires the transfer of tacit knowledge, which is more sensitive to proximity, because of the early stage of university research. However, Mansfield (1995) argued that proximity is more important in applied research collaborations, possibly because face-to-face interaction becomes more useful as research moves closer to application. Santoro and Gopalakrishnan (2001) found that proximity drives greater commercial outcomes at all stages of research.

Acs et al. (1994) concluded that the impact of proximity is greater on smaller firms. The importance of proximity decreases with larger R&D expenditure, suggesting that firms

[25] The studyôs primary measure of prestige was the overall *U.S. News & World Report* graduate school ranking (1991ï 1998).

with greater resources are less geographically constrained (Arundel and Geuna, 2004). Mansfield (1995) found that firms are willing to trade off faculty quality for greater proximity to university collaborators. Lower quality researchers have a relatively low chance of collaborating with firms farther than 100 miles away (Mansfield and Lee, 1996).

The simplest measure of proximity is the physical distance between collaborators. In the case of multi-site firms, the location of the facility involved in the collaboration is typically selected (Acs et al., 1994, Mansfield and Lee, 1996). In addition to distance, Mora-Valentin et al.ôs (2004) Spanish study measured the travel time between collaborators and found that proximity was not important. Alternatively, Beise and Stahl (1999) measured proximity as the number of researchers at public research institutions within 100 miles of the firm and argued that proximity was not as important in Germany as it is in the U.S. Indeed, proximity is a highly relative concept that is dependent on several factors such as political geography and infrastructure (Mora-Valentin et al., 2004).

Research Stage: The stage of research is also considered an important factor in many studies. The Frascati Manual (OECD, 2002) divides R&D into basic research, applied research and experimental development. Using this scheme, Gulbransden and Smeby (2005) found that researchers who receive industry funding are more likely to categorise their research as applied. Rahm et al. (1988) also found empirical evidence of a positive relationship between faculty involvement in industry and applied research. University research is generally considered more basic than applied in nature (Thursby et al., 2001) and the extent to which basic research can generate commercial outcomes has been questioned (Bozeman, 2000). However, Rogers and Bozeman (1997) found that basic research projects have higher costs, but also have a greater likelihood of commercialisation.

Similarly, Gulbrandsen and Smeby (2005) found evidence of a link between basic research and commercialisation across several academic fields but concede that the technological disciplines in Norway are considered ñless basicò than those in other countries. The usefulness of categorising research by stage can be limited by the broad interpretation of the research categories. Calvert (2004) demonstrated the ambiguity of the term ñbasic researchò by identifying six different definitions used by researchers in a variety of contexts.

Project Duration: The duration of a research collaboration is another consideration, although very little is known about its impact on a UIRCôs commercial outcomes. Ambos et al. (2008) found no significant relationship between a UIRC projectôs duration and its commercial outcomes. Lee (2000) found that a longer project duration was significantly and positively associated with greater entrepreneurial opportunity[26].

3.7.5: Research Methodology in University Entrepreneurship

Rothaermel et al.ôs (2007) comprehensive taxonomy of the literature on university entrepreneurship, which included the 173 studies conducted in this field between 1981 and 2005, found that ñmost studies on university entrepreneurship tend to be more qualitative in natureé ò. They found that over half (54 percent) of these studies used qualitative research methods, while 39 percent applied econometric analysis to quantitative datasets. Rothaermel et al. (2007) further found that ñvery few theory-only papers (4 or 2 percent) or

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[26] Lee (2000) created a factor variable called ñBenefits to Entrepreneurial Opportunityò that included the categories 1) Test the practical application of theory, 2) Contribute to the development of patents, and 3) Open business opportunities.

literature reviews (9 or 5 percent) have been publishedò, which signaled a field of study that remains atheoretical and embryonic. However, Rothaermel et al. (2007) did note that the proportion of studies that employed quantitative research methods was considerably larger in the period from 2001-2005 than in the period before 2000, an indication that the field of study is maturing. ñAs a field develops beyond the embryonic stage, researchers tend to shift from more qualitative studies to more quantitative ones, a pattern consistent with the one observed in mainstream management journalsò (Rothaermel et al., 2007).

More recently, Perkmann et al.ôs (2013) literature review on university-industry relations found that ñthe number of articles addressing particularly academic engagement has increased significantly since 2005ò. However, they further point out that poor availability of data in this field of study continues to create methodological limitations that influence not only research questions, but also the unit of analysis on which the research is based, the measures used, and the interpretation of results.

Ambos et al. used Binomial Logit (BNL) to test their hypotheses on the aspects of UIRCs that are associated with commercial outcomes. Their study used the total count of patents, licenses and startups generated from 207 UIRCs in the UK as a binary dependent variable (patent, license or startup from UIRC = (1), no commercial outcome from UIRC = (0)). Their 19 independent variables represented various aspects of the university and the researcher, as well as several control variables. The UIRCs under observation by Ambos et al. (2008) were funded by a premier funding agency in the UK under a program designed to support high-quality UIRCs in technology-related fields.

Most other studies focus on the university as the unit of analysis (50 percent of studies), with the next largest segment of studies focused on the firm as the unit of analysis

(23% of studies) (Rothaermel et al., 2007). For both of these segments, Rothaermel et al. (2007) found that the most common source of data was surveys and direct interviews with key staff in the universities or firms. ñIt is clear that relying on self-reported information is fraught with specific challenges which future work should address in order to improve the quality, reliability and validity of research results.ò (Perkmann et al., 2013). Perkmann et al. (2013) also found that ñall largescale survey-based studies are based on cross-sectional data and therefore pose limitations in terms of inferring causal relationships between variables.ò

Of the studies included in Perkmann et al.ôs (2013) review, 63.9 percent used some form of regression analysis, 22.2 percent were descriptive in nature, 8.3 percent used qualitative methods, and 5.6 percent used network analysis. Rothaermel et al. (2007) found that regression analysis has been used most often to study the productivity of university technology transfer offices, while qualitative methods have been used most often to study university-based startups. These methodological choices are driven in part by the availability of data on technology transfer from sources such as the Association of University Technology Managersô annual survey, compared to the relatively sparse data available on university-based startups. ñThe choice of methods appears to be not only a reflection of the underlying research questions, but also conditioned upon the availability of appropriate dataò (Rothaermel et al., 2007).

Obviously, records held by universities and firms on their interactions would be ideal sources of data, but they are generally not made available to researchers for confidentiality or competitive reasons. Even when available, inconsistencies in how such data are captured make it difficult to standardise over a large number universities and firms

(Perkmann et al., 2013). Therefore, researchers do their best using the data that are available or obtainable, leading to many studies focused on specific industries, geographies, universities or other target groups, with most using different measures that make it difficult to compare results across studies (Perkmann et al., 2013). In their review of the papers in the special section of the journal *Research Policy* marking the 30th anniversary of the Bayh-Dole Act, Grimaldi et al. (2011) remarked: ñOne methodological problem highlighted by papers in this special section concerns access to suitable data that does not just relate to the right hand end of the distribution, for example, in terms of the most successful universities or the most successful forms, of technology and knowledge transfer. This is an important issue if the conclusions of studies are meant to be generalisable both academically and for policy.ò

3.8: Chapter Summary

This study explores the relationship between the characteristics of UIRCs and the commercialisation of their results. Therefore, Section 3.2 described how the study lies at the intersection of the academic literature on 1) university research and development, including UIRC and 2) university technology transfer and commercialisation. Bozeman et al. (2013) proposed an important framework for organising the literature in the field of university research collaboration based on the attributes of the stakeholders and the type of outcomes. Previously, Bozeman (2000) had proposed the Contingent Effectiveness Technology Transfer Model for organising the literature on university technology transfer, which identified the various actors and mechanisms of technology transfer, and criteria for success. Both contributed to setting the appropriate boundary conditions for the literature review described in Section 3.3.

Ambos et al. (2008) was the only study found that investigated the relationship between the characteristics of stakeholders in a UIRC and the commercialisation of its results. The focus of Ambos et al.ȯs study was understanding ambidexterity in research institutions rather than effective commercialisation of UIRC results. As a result, their dependent variable did not distinguish between outcome types, and their independent variables were related primarily to the university and researcher involved in the UIRCs rather than to the firm or the project structure. Nevertheless, Ambos et al. (2008) helped inform this studyȯs research questions and the methodology used to address them.

Sections 3.4, 3.5 and 3.6 described the theoretical foundation of three important factors that influence the commercialisation of UIRC outcomes. Section 3.4 discussed how the concept of embeddedness seeks to explain the role of social networks in economic behaviour. Ambos et. al (2008) used a novel form of structural embeddedness to show the relationship between a researcherȯs career path in academia and the commercialisation of UIRC results. Section 3.5 discussed how government subsidies for UIRC create incentives for firms and crowd-in greater firm contributions. The amount and type of firm contribution to a UIRC may influence the commercialisation of its results. Section 3.6 discussed the theory of absorptive capacity, and how research intensity influences the ability of firms and industries to identify, assimilate and exploit external knowledge. There are considerable sectoral differences in engagement with universities, and in university technology transfer to different industries. Also, there is empirical evidence in the extant literature that a number of other factors may influence university-industry interaction and university technology transfer performance, which are discussed in Section 3.7.

The literature review provided a theoretical basis for some of the characteristics described in Chapter II on Canadaȏs national innovation system, and helped to define a number of research questions, discussed in the next chapter, that have yet to be addressed in the literature.

CHAPTER IV: RESEARCH QUESTIONS

The purpose of this study was to explore the characteristics associated with achieving commercialisation from university-industry research collaborations (UIRCs), and the extent to which these characteristics influence commercial outcomes. The study bridges the gap between the literature on university research and the literature on university technology transfer by exploring how the characteristics of later-stage applied research collaborations such as UIRCs are associated with early-stage commercial outcomes.

Government agencies that provide subsidies in support of UIRCs must evaluate project proposals in order to select the UIRCs with the greatest likelihood of commercialisation. These government agencies could make better funding decisions if they had a better understanding of the factors that lead to the commercial outcomes they seek. These government granting agencies, and by extension the government policy makers that fund them, are the audience for this study. Therefore, the practical business question addressed by this study is: ñamong dozens of funding proposals received by government granting agencies each year, which UIRC projects should be subsidised in order to maximise the chance of commercialisation?ò More specifically, this study aimed to address the following questions:

1. Which characteristics are associated with commercialisation from UIRC, and to what extent do these characteristics contribute to the chance of commercialising its results?
2. Which characteristics are associated with specific types of commercialisation of UIRC results, and to what extent do these characteristics contribute to the chance of each type of commercial outcome?

Question 1 sought to determine what types of universities, researchers and firms were associated with commercialisation of UIRC results and moreover, what project characteristics were associated with commercialisation. Such insights would allow funding agencies to improve their project selection processes by targeting stakeholders with a greater likelihood of commercial outcomes. Question 1 also explored the extent to which these characteristics contribute to UIRC commercialisation, which would shed light on whether some characteristics, or groups of characteristics, are more important to commercialisation than others.

Question 2 sought to determine which characteristics were associated with specific commercial outcomes, such as startup companies and licenses, and explored the influence of these characteristics on the likelihood of each outcome. Such insights would allow fund granting agencies to redesign programs to maximise the potential for specific types of commercial outcomes.

4.1: Conceptual Model

Figure 4.1 is a conceptual model that illustrates how UIRC outcomes are commercialised. The conceptual model is based on the specific Canadian context for this study as described in Chapter II, and is informed by the prevailing academic theory as discussed in Chapter III.

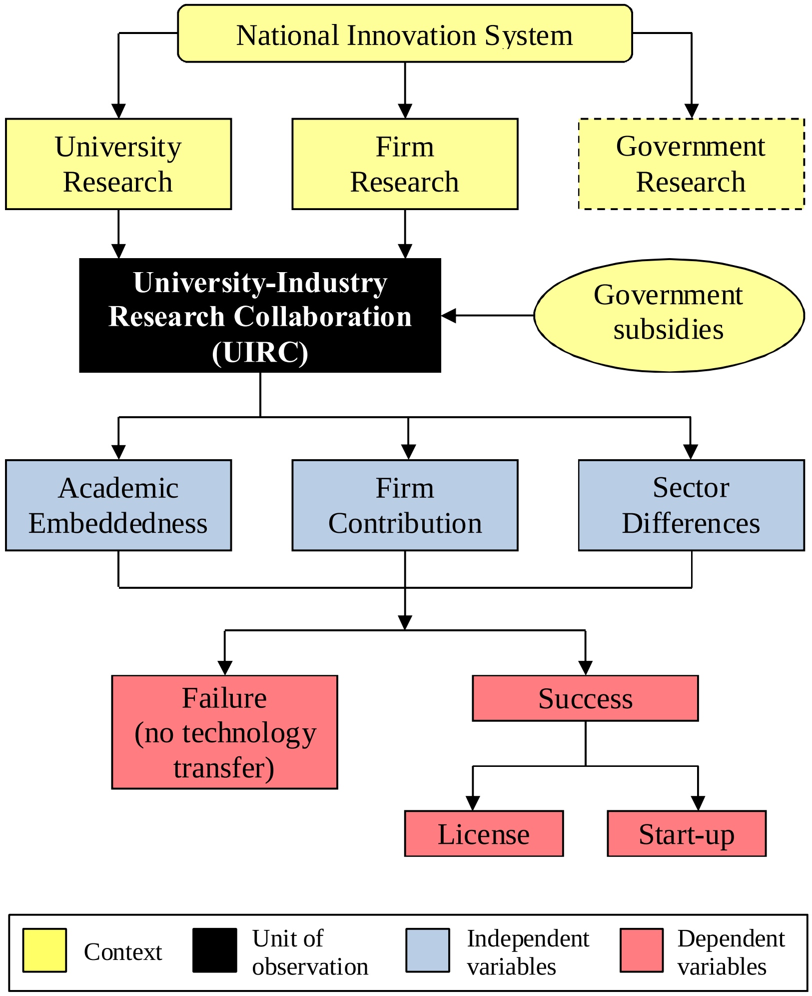

Fig. 4.1: Conceptual Model of UIRC Commercialisation

4.1.1: Canadian Context

The Canadian innovation system involves a unique set of institutions and policies that interact to generate innovation activity (Niosi, 2008). Canada has particularly strong economic, political and cultural ties to both the United States and the United Kingdom, with one foot in the traditions of each country. Resource exploitation plays an important economic role due to Canadaơs abundance of resources. Ontario is Canadaơs manufacturing heartland with particular strength in transportation services (automotive and aerospace) and Information and Communications Technologies (ICT). Manufacturing sales declined in Canada from 1999 to 2009, while the ICT sector grew in relative importance over the same period, underscoring a structural shift from industrial to knowledge-based industries.

Canada has invested considerably less in research and development as a proportion of GDP than many other OECD countries, which is largely attributable to low firm research intensity and suggests low absorptive capacity among Canadian firms (Cohen and Levinthal, 1990). However, this is also largely due to differences in the research intensity of certain Canadian industries compared to other countries. Research intensity was highest in the Canadian ICT sector and was considerably higher than that of U.S. ICT firms. However, research intensity was negligible in the Canadian automotive sector in comparison to the U.S.

Although the production, diffusion, adoption and mastery of technology are generally undertaken by firms, research undertaken by universities is becoming an increasingly important source of innovation (Perkmann et al., 2013, Leydesdorff, 2013, Bozeman et al., 2013, Gibbons et al., 1994). This is especially true in Canada, where universities represent 35 percent of national expenditures on research (Statistics Canada, 2009). In comparison, the United States Department of Commerce (2010) reported that the higher education sector represented 9.3 percent of national research expenditures in 2007. Canadaǿs expenditures on university research are second highest in the OECD relative to GDP. However, there is vast disparity in the scale, reputation and commercialisation output of Canadian universities.

In order to improve private sector research intensity, Canada offers among the highest rates of government support for firm research and development in the world. Indirect tax incentives represent the vast majority of this support. A complex myriad of direct support programs also exists, including programs that support UIRCs specifically.

4.1.2: Unit of Observation

As basic research becomes more applied, interaction between universities and industry increases. These interactions can be informal or formal in nature. Formal collaboration mechanisms include research contracts, faculty consulting and university-industry research collaborations (UIRCs). In this study, the unit of observation was formal UIRCs.

UIRC is an important channel for knowledge transfer within the Canadian innovation system. Since the late 1980s, UIRC has been highlighted as an increasingly important policy priority in government white papers, budgets and programs. UIRC support programs such as the national Networks of Centres of Excellence (NCE) and the provincial Ontario Centres of Excellence (OCE) help strengthen research networks in key industries of strategic importance and provide subsidies for UIRC projects. As a result, firms fund a relatively higher proportion of Canadian university research, and Canadian universities perform a relatively higher proportion of firm research than in the U.S. and U.K. This provides evidence that Canadaôs generous subsidies for UIRC help stimulate, or ñcrowd-inò, firm support for university research (Buisseret et al., 1995).

4.1.3: Dependent Variables

UIRCs can have a number of outcomes (Bozeman et al., 2013); ñknowledge-focusedò outcomes include publications and skills development, while ñproperty-focusedò outcomes include patents, technology licenses or startups. Property-focused outcomes were the subject of interest in this study, particularly licenses and startups. The study was concerned with whether a license or a startup was created following a UIRC to commercialise its results. It was not concerned with the extent of the commercialisation but only that a commercial outcome occurred. This was consistent with what Bozeman (2000) called the ñout the doorò criterion.

Ambos et al. (2008) was the only study found that specifically examined the likelihood of commercial outcomes with UIRCs as the unit of observation. Consequently, it is of considerable importance to the research design and methodology of this study. Ambos et al.ôs (2008) dependent variable measured patent, license and startup counts. There was no consideration of the magnitude or impact of the commercial outcome; their study only counted whether these outcomes occurred or not. Also, Ambos et al. (2008) used a dichotomous dependent variable. All projects that generated a patent, license or startup were coded as (1) while those that did not were coded as (0). However, different factors may lead to different types of outcomes. Ambos said: ñFuture research might, however, usefully look at the different conditions that give rise to each different activity.ò (Ambos et al., 2008, p. 1443). Therefore, this study investigated the different characteristics associated with licenses and startups, respectively.

Once completed, UIRC projects have either failed or succeeded in achieving a license or a startup. Although the commercialisation performance of Canadian universities is generally considered poor relative to other countries, Canadaøs performance may actually be comparable to the U.S. and the U.K. when appropriately controlling for the scale and policies of each university system (Currie and Standards, 2011).

Ultimately, the conceptual model outlines the contextual environment of the study, clarifies the theoretical foundation for the research questions, and substantiates the motivations for the specific hypotheses to be tested.

4.2: Hypotheses

Based on the conceptual model, three hypotheses were developed and tested in this study. The hypotheses centre around important factors that were found to be associated with UIRC commercialisation in the literature, and that are worthy of further investigation in the Canadian context of this study.

4.2.1: Hypothesis 1 – Embeddedness

A university researcherøs academic career is to some extent ñpath dependentò, which is induced by the requirements of the profession to conduct research and disseminate the results, and by the relatively hierarchical structure of universities. Over the course of their academic careers, researchers accumulate human and social capital that contributes to their advancement (Bozeman and Corley, 2004). As researchers gain experience, they cultivate the expertise required to succeed in academia, develop their reputations, and further advance in their careers. Researchers who struggle to succeed or to adapt to the academic culture may leave to pursue careers in industry (Lam, 2005). Over time, the remaining researchers become increasingly entrenched in the culture and mindset of academic research. Older, more senior researchers may resist attempts to modify the current academic system that has led to their success to date (Markides, 2007). In contrast, younger researchers with less career advancement may be more entrepreneurial since they are not yet fully indoctrinated within traditional academic culture and have been trained to be more open to commercialisation. This suggests a split between ñold schoolò and ñnew schoolò researchers based on their level of embeddedness in academia, and the emergence of ñstarò researchers who are sufficiently ambidextrous to succeed at both academic and commercial activities.

The concept of embeddedness has been applied in many contexts to explain how social networks affect economic behaviour. Several studies in the university research and university technology transfer literature have explored related concepts (Boardman, 2008, 2009, Boardman and Corley, 2008, Ponomariov and Craig Boardman, 2008, Bozeman and Gaughan, 2007, Dôeste and Perkmann, 2011, Haeussler and Colyvas, 2011, Link et al., 2007). Ambos et al. (2008) used a novel operationalisation of structural embeddedness to investigate how a researcherôs career position affects the commercialisation of UIRCs in the U.K. Their study found a strong negative association between embeddedness and commercial outcomes from UIRCs. However, the relationship between embeddedness in Canadian universities and UIRC commercialisation is not known, given the unique role that universities play in Canadaôs national innovation system. Building on the embeddedness literature, and following Ambos et al.ôs operationalisation of the concept, this study hypothesised that commercial outcomes from UIRCs will be negatively associated with researcher embeddedness within academia.

Hypothesis 1: UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.

4.2.2: Hypothesis 2 – Firm Contribution

Research is important to national productivity and competitiveness (Arrow, 1962); therefore governments subsidise private sector research to increase the private rate of return on research to match the rate of return to society (Griliches, 1979). UIRC is an increasingly important mechanism of research collaboration and technology transfer supported by governments. Canadaôs support for university-industry research collaboration (UIRC) is particularly strong, ranking first among the G7 countries (Hanel and St-Pierre, 2006). University researchers are under increased pressure to raise industry funding to bolster their research budgets (Kesting et al., 2014). Increasing university commercialisation activity also creates additional incentive for researchers to collaborate with industry (Perkmann et al., 2013). Firms seek to de-risk their research by cost sharing with universities and government granting agencies. Financial constraints within the firm can make research collaboration more attractive, especially if further subsidised by government.

The concept of crowding-in suggests that government funding for research will have a ñcomplementaryò effect on industry research funding. Crowding-in/out is a concept widely used in economics to explain the effect of government involvement in a sector of the market economy (Spencer and Yohe, 1970). The academic literature is split on whether government subsidies complement or substitute private research expenditures. However, there is mounting evidence in more recent studies that government subsidies help to stimulate greater private sector research.

Firms that engage in UIRC often use competitive processes, of varying levels of formality, to identify the collaborations that best meet their objectives. The level of government subsidy or firm contribution to a UIRC may influence its commercial outcomes. However, few studies have investigated how the amount contributed by a firm influences a UIRC. Ambos et. al (2008) simply measured the presence of a firmÕs cash contribution to a UIRC (not the amount of the contribution) and found no significant relationship with commercial outcomes. In addition to the amount of firm contribution to UIRCs, cash or in-kind contributions may each have a different effect on commercial outcomes. Government granting agencies seek higher contributions from firms to UIRCs because higher contributions embody a greater level of crowding-in, represent more efficient use of government subsidies, and demonstrate a stronger interest on behalf of the firm in the research, and by extension, in the commercialisation of its results. Building on the crowding-in literature, this study hypothesised that commercial outcomes from UIRCs will be positively associated with higher cash and in-kind contributions by firms.

Hypothesis 2: UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes.

4.2.3: Hypothesis 3 – Industry Sector

A firmÕs research intensity can influence its absorptive capacity, defined as the ability to identify, assimilate and exploit external knowledge (Cohen and Levinthal, 1990). As previously discussed, the research intensity of Canadian firms is low when compared to other industrialised countries. However, CanadaÕs research intensity in certain key knowledge-based industries is on par or higher than that of U.S. As predicted by the theory of absorptive capacity, different industries have adopted unique patterns of engagement with universities in research and commercialisation activities (Perkmann et al., 2013). Several studies in Canada, the U.S. and Europe have found evidence that industry sectors with higher research intensity, such as biotechnology and ICT, tend to engage more with universities (Geiger, 2012, Grossman et al., 2001). University commercialisation performance is also greater in sectors with high absorptive capacity (Landry et al., 2006). However, Ambos et al.ôs (2008) study of UIRCs in engineering and physical sciences in the U.K. used a control variable for each science field but found no significant relationship with commercial outcomes. Building on the absorptive capacity literature, this study hypothesised that commercial outcomes from UIRCs will be more likely in industries with higher research intensity.

Hypothesis 3: UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.

4.3: Chapter Summary

The purpose of this study was to explore the characteristics associated with achieving commercialisation from university-industry research collaborations (UIRCs), and the extent to which these characteristics influence commercialisation. A conceptual model was presented that illustrates how UIRC outcomes are commercialised based on the specific Canadian context for this study and the prevailing academic theory.

Based on the conceptual model, three hypotheses were developed and tested in this study. The hypotheses centre around important factors that were found to be associated with UIRC commercialisation in the literature, and that are worthy of further investigation in the Canadian context of this study.

The relationship between a researcherôs embeddedness in Canadian universities and UIRC commercialisation is not known, given the unique role that universities play in Canadaôs national innovation system. Building on the embeddedness literature, and following Ambos et al.ôs operationalisation of the concept, this study hypothesised that commercial outcomes from UIRCs will be negatively associated with researcher embeddedness within academia.

Hypothesis 1: UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.

Government granting agencies seek higher contributions from firms to UIRCs because higher contributions embody a greater level of crowding-in, represent more efficient use of government subsidies, and demonstrate a stronger interest on behalf of the firm in the research, and by extension, in the commercialisation of its results. Building on the crowding-in literature, this study hypothesised that commercial outcomes from UIRCs will be positively associated with higher cash and in-kind contributions by firms.

Hypothesis 2: UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes.

University commercialisation performance is greater in sectors with high absorptive capacity based on their research intensity. Building on the absorptive capacity literature, this study hypothesised that commercial outcomes from UIRCs will be more likely in industries with higher research intensity.

Hypothesis 3: UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.

Next, the methodology chapter with discuss the chosen research design and rationale, the source of data, and how it was collected and operationalized to address the research questions.

CHAPTER V: METHODOLOGY

The methodology chapter outlines a research design that is appropriate for the research questions and the hypotheses described in Chapter IV. It also discusses how the studyŝ data was sourced, collected and prepared. Finally, it describes how the data was operationalised into dependent and independent variables to test the hypotheses.

5.1: Introduction

Section 5.2 provides a description of the correlational research design selected for this study and why it is appropriate for determining the factors associated with commercial outcomes from UIRCs.

Section 5.3 describes the studyŝ primary data source from the Ontario Centres of Excellence, including its programs, industry sectors, and selection process.

Section 5.4 describes other sources used to assemble the studyŝ novel dataset.

Section 5.5 defines each measure used in the study in detail, including the two dependent variables that represent different University-Industry Research Collaboration (UIRC) outcomes, the five independent variables used to test the hypotheses, and the 19 control variables that represent different characteristics of the UIRC.

Section 5.6 explains the procedures followed in order to create the sample of 682 UIRCs, along with the five steps followed to collect the necessary data on the sample.

Section 5.7 discusses the methods used to address the missing data in three independent variables.

Section 5.8 provides descriptive statistics to help elucidate and summarise the data.

5.2: Research Design

Selection of the appropriate research design, data collection procedures and analysis techniques were dictated by the nature of the research questions (Kerlinger and Lee, 2000). The studyôs research questions seek to explore the extent to which commercialisation from UIRC is a function of the characteristics of its stakeholders, or of different combinations thereof. In addition, the study seeks to test three hypotheses motivated by prevailing theories in the extant literature and the unique features of the Canadian innovation system.

$$P_{commercialisation} = \int \left\{ \begin{array}{l} university \\ researcher \\ firm \\ government \end{array} \right\}$$

The study employed a correlational research design involving the quantitative analysis of the data to explore the nature of the relationships among the variables.

5.3: Source of Data

The study made use of secondary data collected from OCEôs historical records and other public sources. Data was collected on UIRC projects supported by OCE between 2000 and 2009, and was composed of pooled cross-sectional, time-series data. The data included information captured at the time the OCE-supported UIRC projects were conceived. Although the dataset included measurements from UIRC projects conceived over several years, each project was measured only once and not over time.

5.3.1: Description of the Ontario Centres of Excellence[27]

OCE is a granting agency that provides government funding for UIRC projects. OCE is a not-for-profit organisation created in 1987 to support research collaboration between universities and industry in the province of Ontario, Canada. As described in Chapter II, Ontarioǿs economy began an ongoing shift in the 1980s from a traditional resource and manufacturing-based economy to one that was becoming increasingly knowledge-based.

Although universities in Ontario were conducting high quality scientific research, policy makers believed that the results of this research were not being commercialised to their full potential by industry. OCE was designed to support productive research networks and partnerships between universities, colleges, research hospitals and Ontario industry.

Throughout most of its history, OCE has been organised around key technology areas of strategic importance to the province of Ontario, which are concentrated primarily in the physical sciences and engineering. OCE was originally conceived with seven independent technology centres, which evolved and were amalgamated into four centres in 1999. Ontario Centres of Excellence Inc. was created in 2004 as a single entity with four sector-focused divisions: communications and information technology; earth and environmental technologies; materials and manufacturing; and photonics.

OCE delivers three categories of programs:

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[27] The description in this section of OCE, its history, its mandate and its programs was adapted from the organisationǿs 2009-2010 Annual Report. The description also includes information from internal historical documents obtained from OCE.

1. **Research programs** provide funding support for research collaborations between academia and industry. OCE's desired outcomes for these projects are licenses and startups.
2. **Commercialisation programs** provide funding support for further technical and market development of a university technology. OCE's desired outcomes for these projects are technical proof-of-principle and customer engagement.
3. **Talent programs** provide funding support for fellowships and internships. OCE's desired outcome for these projects is knowledge transfer through highly qualified people.

Over the 2009/2010 fiscal year, OCE invested $25.8 million in 503 research, commercialisation and talent projects and leveraged $40.1 million from industry partners.

Data on OCE's research programs was ideally suited for the purpose of this study since they have formalised programs to support UIRCs with a consistent structure (Santoro and Gopalakrishnan, 2001, Betz, 1996, Geisler, 1995) and have an explicit mandate to commercialise project outcomes.

5.3.2: OCE Industry Sectors[28]

From 1987 to 2004, OCE existed as an umbrella organisation that was composed of multiple independent centres, each focused on a key industry sector of strategic importance to the province of Ontario. The centres shared a common mandate to support collaborative research, commercialisation of technology and training for highly qualified personnel.

[28] The description in this section of OCE's corporate structure and centres was adapted from the organisation's 2002-2004 Annual Report Summary.

From 1999 until 2004, OCE was comprised of four centres. These centres are represented by the variable *Research Field*, described in Section 5.5.5.

Communications and Information Technology Ontario (CITO) worked to foster critical links between the industry/business community and academic research in information technology, telecommunications and digital media sectors.

The *Centre for Research in Earth and Space Technology* (CRESTech) focused on investing in multidisciplinary collaborative research and development in clean air and energy, clean water, sustainable agriculture, sustainable infrastructure, and niche technologies within Ontarioǿs environmental, resource management and space sectors.

Materials and Manufacturing Ontario (MMO) took the lead in developing new knowledge and technology relevant to needs, now and in the future, of Ontarioǿs materials and manufacturing industry.

Photonics Research Ontario (PRO) focused its research and development efforts on photonicsð the generation, transmission, storage and detection of lightð and biomedicine, seeking a competitive edge for Ontarioǿs industrial sector in the generation and harnessing of light and other forms of radiant energy.

On April 1, 2004, these four centres formally merged to become a new corporate entity, Ontario Centres of Excellence Inc. The four original centres subsequently became four divisions within OCE Inc., with each division led by managing directors reporting to OCE Inc.ǿs President and CEO.

5.3.3: OCE Programs

Over the time horizon for this study, OCE provided financial support to hundreds of UIRC projects each year. Projects were funded under several programs, which had slightly different characteristics. The programs that focused on generating commercial outcomes through licenses or startups were 1) the Collaborative Research program; 2) the Technical Problem Solving program; and 3) the Proof-of-Principle program. These programs are represented by the variable *Stage*, described in Section 3.4.5.

> *Collaborative Research Program:* Designed for earlier-stage projects with applied technical research challenges, demonstrated market pull, and high potential for commercialisation.
>
> *Technical Problem Solving Program:* Supported short-term projects and collaboration between industry and academia to build partnerships that addressed mid-stage research challenges, yielded commercial results and provided hands-on problem-solving experience.
>
> *Proof of Principle Program:* Supported later-stage technology development and testing in collaboration with industry, and in preparation for commercialisation.

5.3.4: OCE's UIRC Project Selection Process

OCE utilised a comprehensive process for developing, evaluating, selecting and managing the UIRC projects it funded. The objective of this process was to select the projects most likely to generate commercial outcomes, namely licenses or startups. The sample of UIRC projects used in this study was subject to this selection process. Therefore, its results should be interpreted in the following context:

> *Project Development:* OCE solicited UIRC project funding applications through a periodic Call for Proposals process, typically several times per year. When a Call for Proposals was made, OCE's business development officers played the lead role in proactively identifying potential partners for UIRC projects. Over a period of weeks or months, OCE would work closely with these potential partners to scope out the goals of the project, the roles and responsibilities of the partners, and the project deliverables, milestones and budget. The best of these would ultimately be developed into UIRC project proposals submitted by the partners prior to the posted deadline.
>
> *Project Review:* OCE undertook an initial screening of the submitted proposals to ensure that all required information was included, and that the project activities and budget were in line with the program's criteria. A summarisation and analysis of key information would be conducted and assembled into proposal packages to help facilitate an expert review.
>
> *Expert Review:* The proposals were then subjected to review by a panel of experts from industry, government and the academic community. Panelists were free of conflict of interest and were selected for their ability to evaluate the proposals based on their technical merits and their business case. Panelists would first provide blind scores and comments on each proposal and would then assemble to discuss the proposals in a panel meeting, during which final recommendations were made.

Project Management: Based on the recommendations of the expert panel, OCE managed the process of launching the selected projects and would then track their progress, milestones and budgets over time. At their conclusion, OCE managed the project outcomes to maximise the potential for the commercialisation of any subsequent intellectual property.

5.3.5: OCE Data Access

Data were collected on the projects themselves, on their participants, on their evaluation and selection, on their management, and on their outcomes. These data are maintained as part of OCEØs historical records and are available for some projects dating from as early as 2000.

Discussions with OCE began in October 2009 regarding the potential to conduct a research study using data from the organisationØs historical records. In February 2011, following the completion of a feasibility study, a research proposal was submitted to OCE for consideration. The proposal was accepted by OCEØs executive in March 2011.

5.3.6: OCE Data Usage

A comprehensive Data Use Agreement was executed with OCE in April 2012. The Data Use Agreement conferred the right to use and disclose data provided by OCE for research purposes as described in the research proposal, subject to a number of terms and restrictions. The data must be held in confidence and may not be disclosed in any manner whatsoever, with the exception of conditional disclosure to academic advisors. Copies of the data or work derived from the data, such as variables, may not be provided to any other individual or organisation.

The agreement outlined a number of administrative, technical, procedural, and physical safeguards to be employed to protect the data, and to prevent unauthorised access and use, including:

- an accurate written account of all authorised copies of the data was kept and could be provided to OCE upon request;
- in the case where data was stored in digital form on a computer, the use of the computer must be restricted by password;
- any back-up copies of data in digital form were stored in compressed format and password protected;
- in the case where data was contained in printed documents, such documents were kept in a locked drawer or file cabinet when not being referenced; and
- any printed documents containing data that were no longer needed were shredded before disposal.

Any research results arising from the study may be published, provided that no individual, family, household, business, or organisation is identified, with the exception of OCE. The use of the data was consistent with the policies set out by the University of Reading's Research Ethics Committee.

OCE may request that all data be returned to OCE or certified in writing to have been destroyed or deleted within thirty days following the completion of the study or the termination of the agreement.

The Data Use Agreement is provided in Appendix A.

5.4: Other Data Sources

The data collected from OCE-supported UIRCs projects were then complemented by additional data gathered from five other sources. The data were typically gathered manually and added to each observation one variable at a time.

Data obtained from OCE was supplemented by data from the following publicly available sources[29]:

> *Intellectual Property Policies:* Inventions made at any public research institution in Ontario are governed by the IP policies of that institution. These policies are publicly available and typically published on the institutionǿs website. A report published by the Centre for Policy Research on Science and Technology (CPROST) at Simon Fraser University (Hen, 2010) was also used as a reference guide for the IP policies of the institutions included in this study.
>
> *Maclean's Magazine Reputational Survey of Canadian Universities:* This survey is conducted as part of Macleanǿs annual ranking of Canadian universities. The ranking was first published in 1991. The reputational survey aims to reflect a universityǿs reputation in the community at large. The survey is sent annually to more than 11,000 individuals, including university officials, high school principals and guidance counselors, heads of national and regional organisations, CEOs and recruiters.

[29]: A project proposal was submitted to Statistics Canada for access to their Survey of Intellectual Property Commercialisation in the Higher Education Sector survey, which contains data on a number of academic technology transfer activities in Canada. Unfortunately, the survey in question was not among those available for public research purposes. Therefore the project proposal was rejected.

Research Infosource ranking of Canada's Top 50 Research Universities: Research Infosource Inc. is a consulting and research services firm with a specialisation in the Canadian R&D ecosystem. Research Infosource publishes a number of reports that highlight research and development at Canada's most innovative universities, corporations, hospitals and colleges, including an annual ranking of Canadaǒs Top 50 Research Universities.

Association of University Technology Managers (AUTM) Canadian Licensing Activity Survey: AUTM is a nonprofit organisation dedicated to supporting and enhancing the global academic technology transfer profession through education, professional development, partnering and advocacy. The AUTM Licensing Activity Survey offers quantitative data and real-world examples about licensing activities at U.S. and Canadian universities, hospitals and research institutions.

Google Maps: Google Maps is a web-based mapping service provided by Google Inc. A number of mapping services are provided free of charge. The study used data from Google Maps to estimate the Distance between two locations in terms of driving distance.

The result is a novel dataset that brings together proprietary data from a government granting agency with publicly available data in a way that offered new insight into the characteristics associated with commercialisation of UIRC results.

5.5: Measure Development

The UIRC project was the unit of observation in the study. The dependent variables represented the commercial outcomes of each UIRC project, namely licenses and startups.

The independent variables represented the characteristics of the stakeholders in each UIRC project. The study includes a total of two dependent variables, five independent variables related to three hypotheses, and 19 control variables. Detailed information on each variable is provided below.

5.5.1: Dependent Variables

The study measured two types of commercial outcomes as dependent variables: licensing of university technology to existing firms; and the creation of university-based startup companies. This does not discount the importance of other types of ñtransfer mediaò (Bozeman, 2000, p. 640), such as informal linkages and personnel exchange (Mowery and Sampat, 2004). However, licensing and startups represent two of the most tangible ñproperty basedò commercial outcomes (Bozeman et al., 2013). They also represent the two commercial outcomes that have been tracked consistently by OCE in its historical records.

This studyôs treatment of commercial outcomes of UIRCs as a dependent variable is consistent with that of Ambos et al. (2008), who used the number of patents, licenses and startups in theirs. This is also consistent with Bozemanôs (2000) ñout-the-doorò criterion for effective technology transfer, which considered only whether or not commercialisation occurred. For the purposes of the study, this implied measuring whether or not a UIRC resulted in a license or a startup. The definition did not consider the impact of the technology transfer, such as the creation of new products, profits or market share changes. Several extraneous factors can contribute to the size and scale of such impacts over time. Using the ñout-the-doorò criterion for effective technology transfer avoided the need to control for the impact of future events that are outside the UIRC stakeholdersô control, and therefore are not relevant to the relationships between the variables in the study.

Table 5.1 summarises alternative measures of the studyǿs dependent variables used in the specification of the model.

Table 5.1: Dependent Variables – Commercial Outcomes

Variable	Name	Description	Measure	Source
Commercial Outcomes by Type	*tttype*	Occurrence of a commercial outcome by type, whether or not to the project partner(s), directly attributable to the observation	Categorical variable 0 = failure 1 = license 2 = startup	OCE Historical Records
Commercialisation	*tttotal*	Occurrence of commercialisation, whether or not to the project partner(s), directly attributable to the observation	Binary variable 0 = failure 1 = success (license or startup)	Computed from *tttype*

Commercial Outcomes by Type: As suggested in Ambos et al.ǿs (2008) recommendations for future work, the study used a categorical variable that measured the occurrence of each type of commercial outcome separately. The source of data for this variable was OCEǿs historical records. The categories represented unordered choices that were finite and mutually exclusive, and represented the exhaustive commercial outcomes possible in the context of this study, namely licenses and startups.

Commercialisation: Following the approach taken by Ambos et al. (2008), the study also used a binary variable that simply measured whether or not commercialisation occurred. The variable was computed by combining the categories in *Commercial Outcomes by Type* to answer yes or no.

5.5.2: Hypothesis 1 - Embeddedness

Hypothesis 1 proposed that UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes. The study also measured a number of control variables related to the researcher involved in a UIRC. For the purpose of this study, the data is related to the Principal Investigator responsible for the UIRC project. It should be acknowledged that other faculty, staff and students may be involved in the project (Beaver, 2001), but no data was available on these participants for the projects under observation. Ambos et. al. (2008) used the characteristics of the Principal Investigator in the URICs, and this approach has been taken in a number of related studies involving researcher characteristic (Dôeste and Perkmann, 2011, Haeussler and Colyvas, 2011, Lacetera, 2009, D'Este and Patel, 2007).

Following Ambos et al. (2008), the concept of embeddedness was measured using two variables: *PhD Age* and *Position*. As described below, the operationalisation of these two variables was slightly different in this study compared to Ambos et al. (2008).

PhD Age: This was a continuous variable that measured the researcherôs ñacademic ageò by counting the number of years between when the researcher earned a doctoral degree and the start date of the UIRC. *PhD Age* was one of two measures of researcher ñembeddednessò used by Ambos et al. (2008), although their study counted the number of years specifically spent in academia by the researchers after completion of their PhD. The source of data for this variable was the researcherøs Curriculum Vitae in OCEøs historical records. Where OCEøs records were insufficient, public data sources such as the researcherøs website were used.

Position: This was an ordinal variable that recorded the researcherøs academic position. *Position* was the other measure of ñembeddednessò used by Ambos et al. (2008). As shown in Table 3.2, this study uses four categories of a researcherøs *Position*, which is more detailed than the binary categorisation (Full Professor = 1, All Other Faculty = 0) used by Ambos et aløs (2008) and Døeste and Perkmann (2011). The source of data for this variable was the researcherøs Curriculum Vitae in OCEøs historical records.

Table 5.2 summarises the variables used to measure embeddedness and the researcher control variables.

Table 5.2: Independent Variables – Researcher Characteristics

Variable	Name	Description	Measure	Source
Hypothesis 1: Embeddedness:				
PhD Age	*profsenior*	Time since researcher earned a PhD	Continuous variable of number of years since the researcher earned Doctorate	Researcher's *Curriculum Vitae* in OCE Historical Records
Position	*proftitle*	Researcher's academic position within the university	Ordinal variable 0 = staff (pdf or adjunct) 1 = mid-level (assistant or associate professor) 2 = full (full professor) 3 = distinguished (distinguished professor)	Researcher's *Curriculum Vitae* in OCE Historical Records

Control Variables:				
Researcher Interaction	*profrecord*	Researcher's past interaction with industry in previous OCE UIRCs.	Continuous variable of the number of OCE UIRCs in which the researcher was previously involved	OCE Historical Records
Gender	*profsex*	The gender of the researcher	Binary variable 0 = male 1 = female	Researcher's *Curriculum Vitae* in OCE Historical Records

In addition to the embeddedness variables necessary to test Hypothesis 1, a number of researcher control variables were included in the model, based on factors found to be associated with UIRC and university technology transfer in the literature.

Researcher Interaction: This was a continuous variable that measured the researcherôs interaction with industry in previous OCE-supported UIRCs. The variable attempted to measure the impact of a researcherôs past UIRC experience on the success of UIRC (Siegel et al., 2004). Data on the researcherôs entire career experience in undertaking UIRCs was not available. As a proxy, the variable measured the number of OCE-funded UIRCs in which the researcher was previously involved. This is similar to the approach in Ambos et al. (2008), who counted the number of previous projects the researcher had received from the same funding agency. The source of data for this variable was OCEôs historical records.

Gender: This was a binary variable that recorded the gender of the researcher. The variable attempted to capture the impact of gender on UIRC success (Tartari and Salter, 2015, Stack, 2004, Xie and Shauman, 1998). The source of data for this variable was the researcherôs Curriculum Vitae in OCEôs historical records.

5.5.3: Hypothesis 2 - Firm Contribution

Hypothesis 2 suggested that UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes. Obviously, the presence of a firm as a stakeholder is what distinguishes UIRCs from other types of university research projects. The inclusion of several firm control variables in this study is an important differentiator from Ambos et al. (2008), and from the broader literature on the commercialisation of university research.

Two variables were created to measure the firmøs cash and in-kind contributions to the UIRC, respectively.

> *Firm Cash:* This was a continuous variable that measured the amount of cash contributed towards the projectøs budget by the firm(s). It represents an important improvement over Ambos et al.øs (2008) binary variable that measured only whether or not a cash contribution was made by the firm to the UIRC. The source of data for this variable was OCEøs historical records.
>
> *Firm In-Kind:* This was a continuous variable that measured the estimated cash value of the in-kind contribution made to a project by the firm(s). It also represents an improvement over Ambos et al.øs (2008), who did not distinguish between cash and in-kind contributions made by firms. The source of data for this variable was OCEøs historical records.

Table 5.3 summarises the variables used to measure firm characteristics.

Table 5.3: Independent Variables – Firm Characteristics

Variable	Name	Description	Measure	Source
Hypothesis 2: Firm Contribution				
Firm Cash	*firmcash*	The amount of cash contributed towards the project budget by firm(s)	Continuous variable in dollars	OCE Historical Records
Firm In-Kind	*firminkind*	The estimated cash value of un the in-kind contribution made by firm(s)	Continuous variable in dollars	OCE Historical Records
Control Variables:				
Firm Size	*firmsize*	Size of the Lead Firm by Employees at the Start Date of the project	Ordinal variable Micro = < 10 Small = 10 - 99 Medium = 100 - 999 Large = > 1000	OCE Historical Records
Firm Interaction	*firmrecord*	Lead Firm's past interaction with researchers in previous OCE-supported UIRCs	Continuous variable of the number of past OCE UIRCs in which the Lead Firm was previously involved	OCE Historical Records
Number of Firms	*firmnum*	The number of firms involved in the project	Continuous variable	OCE Historical records

In addition to the firm contribution variables necessary to test Hypothesis 2, a number of firm control variables were included in the model, based on factors found to be associated with UIRC and university technology transfer in the literature.

Firm Size: This was an ordinal variable that measured the size of the firm at the start date of the project in terms of number of employees. The categorization is based on Statistics Canadaôs classification of business size, with an adjustment to the category ñlargeò from 500 to 1000 employees to better fit the context for this study. The variable attempted to capture how the size of a firmꞌs resources impacts UIRC success (Santoro and Gopalakrishnan, 2001, Cohen et al., 2002). The number of employees was selected rather than annual sales as the measure of size because of the availability of this data in OCEꞌs historical records. In the case of projects that involved more than one firm, data on the lead firm was used.

Firm Interaction: This was a continuous variable that measured the firmꞌs interaction with university researchers in previous OCE-supported UIRCs. The variable attempted to measure the impact of a firmꞌs past UIRC experience on the success of the UIRC under observation. Data on the firmꞌs entire experience in undertaking UIRC was not available. As a proxy, the variable measured the number of OCE-funded UIRCs in which the firm was previously involved. In the case of projects that involved more than one firm, data on the lead firm was used. The source of data for this variable was OCEꞌs historical records.

Number of firms: This was a continuous variable that measured the number of firms involved in a project. The variable attempted to capture the impact of the participation of multiple firms in a UIRC on its commercial outcomes. The source of data for this variable was OCEꞌs historical records.

5.5.4: Hypothesis 3 - Industry Sectors

Hypothesis 3 proposed that UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes. Other characteristics of the UIRC itself can also influence the likelihood of commercialisation. Therefore, a number of control variables related to the structure of the project were also included in the model.

As was the case with this study, Ambos et al. (2008) focused on UIRCs within the fields of physical sciences and engineering. Following Ambos et al. (2008), this study included a variable that represented the UIRCõs industry sector.

Research Field: This was a categorical variable that recorded the research field of the project. The categories corresponded with the sector focus of each of OCEõs four centres/divisions: Communications and Information Technology (CIT); Materials and Manufacturing (MM); Earth and Environmental Technology (EET); and, Photonics. The source of data for this variable was OCEõs historical records.

Table 5.4 summarises the variables used to measure UIRC projects characteristics.

Table 5.4: Independent Variables – Project Characteristics

Variable	Name	Description	Measure	Source
Hypothesis 3: Industry Sectors				
Research Field	*projfield*	Research field of the project	Categorical variable 1 = CIT 2 = MM 3 = EET 4 = Photonics	OCE historical records
Control Variables:				
Research Stage	*projstage*	Stage of the research to be undertaken in the project	Ordinal variable 1 = Earliest 2 = Mid-stage 3 = Latest	OCE historical records
Funding	*projfund*	Project funding awarded by OCE	Continuous variable in dollars	OCE historical records

Length	*projlength*	Total length of the project	Continuous variable in months	OCE historical records
Distance	*projprox*	Physical distance between the researcher and the lead firm	Continuous variable in kilometres	Google Maps and OCE historical records

In addition to the variables necessary to test Hypothesis 3, a number of project control variables were included in the model, based on factors found to be associated with UIRC and university technology transfer in the literature.

Research Stage: This was an ordinal variable that recorded the stage of the research undertaken in the project. The variable attempted to capture the impact of the stage of the research on UIRC commercialisation (Gulbrandsen and Smeby, 2005, Rogers and Bozeman, 1997). The categories corresponded with the programs that support UIRC within OCE, as described in Section 3.3.1. Each program was considered to target a progressively later stage of research: the category *Earliest* corresponds with UIRCs from OCEớs Collaborative Research programs; the category *Mid-stage* corresponds with UIRCS from OCEớs Technical Problem Solving program; and the category *Latest* corresponds with UIRCs from the Proof of Principle program. The source of data for this variable was OCEớs historical records.

Funding: This was a continuous variable that measured the amount of project funding awarded by OCE in dollars. The source of data for this variable was OCEớs historical records.

Length: Following the approach taken by Ambos et al. (2008). This was a continuous variable that measured the total length of the project in months. The source of data for this variable was OCEớs historical records.

Distance: This was a continuous variable that measured Distance in kilometres. The variable attempted to capture the impact of the physical distance between the researcher and the firm on UIRC commercialisation. In the case of projects that involved more than one firm, data on the lead firm was used. In the case of projects that involved more than one academic researcher, data on the principal investigator was used. The source of data for this variable was Google Maps and OCE's historical records.

5.5.5: University Control Variables

The researchers involved in UIRCs are employed by universities, who are also important stakeholders in these projects. Therefore, a number of university control variables were included in the model, representing each university's size, reputation, technology transfer office (TTO) and Intellectual Property (IP) ownership policy.

The majority of the data for these measures was derived from third party surveys taken in 2010.[30] Consequently, the data collected on these university characteristics varied across universities but not over time.[31] This approach is consistent with that of Ambos et al. (2008). Their study used a sample of UIRCs funded over a five year period (1999-2003). However, several of their measures of university characteristics were based on secondary survey data collected in 2001. Evidence suggests that university characteristics should not

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[30] Surveys published in 2010 were used because they are based on 2009 data, which was the year by which the UIRC must have been completed to be included in the sample for this study. This and other sampling criteria are discussed in detail in the next section.

[31] The steps taken to mitigate this data limitation are discussed in Section 4.5 of Chapter IV: Analysis (p. 88).

vary considerably over the time horizon for this study. For example, Lack and Schankerman (2004) found that seventy percent of respondent universities in their study had not changed their royalty distribution policy over the nine year period of the study.

Table 5.5 summarises the control variables used to measure each universityôs characteristics. These variables are based on factors found to be associated with UIRC and university technology transfer in the literature.

Table 5.5: Independent Variables – University Characteristics

Variable	Name	Description	Measure	Source
Controls of University Size:				
Research Capacity	*unires*	University's total expenditures on research and development in 2010	Continuous variable in dollars	Research Infosource ranking of Canadaôs Top 50 Research Universities
University Faculty	*uniprof*	Universityôs total number of full-time faculty members in 2010	Continuous variable	Research Infosource ranking of Canadaôs Top 50 Research Universities
University Operations	*uniops*	The Universityôs operational expenditures per student in 2010	Continuous variable in dollars	Macleanôs Magazine Survey of Canadian Universities 2010
Controls of University Reputation:				
Reputation Ranking	*unirepont*	Universityôs rank among Ontario universities based on its reputation in 2010	Ordinal variable of university rankings	Macleanôs Magazine 2010 Survey of Canadian Universities
Research Ranking	*unirdont*	Universityôs rank among Ontario universities based on dollar value of research grants received in 2010	Ordinal variable of university rankings	Macleanôs Magazine 2010 Survey of Canadian Universities
Faculty Awards	*uniaward*	Number of awards received per 1,000 faculty in 2010	Continuous variable in numbers	Macleanôs Magazine 2010 Survey of Canadian Universities
Controls of TTO:				

Invention Disclosures	*ttoinvent*	Number of inventions disclosed to the University in 2010	Continuous variable in numbers	AUTM Canadian Licensing Activity Survey 2010
TTO Staff	*ttostaff*	The number of full-time employees involved in technology transfer in 2010	Continuous variable in numbers	AUTM Canadian Licensing Activity Survey 2010
TTO Experience	*ttoexper*	Years since the University's technology transfer program started	Continuous variable in years	AUTM Canadian Licensing Activity Survey 2010
IP Ownership	*uniip*	Ownership of intellectual property created at the University	Categorical variable 0 = university 1 = creator	University Intellectual property policies

University Size: The size and scope of a university's resources can impact commercialisation (Wright et al., 2004). Three alternative measures of university size were used in this study. *Research Capacity* was a continuous variable that measured the university's total expenditures on research development in dollars. *University Faculty* was a continuous variable that measured the number of full-time faculty employed by the university. The source of the data for these variables was the Research Infosource ranking of Canada's Top 50 Research Universities. *University Operations* was a continuous variable that measured the university's operational expenditures per student in 2010. The source of the data for this variable was Maclean's Magazine 2010 Survey of Canadian Universities.

Reputation: Three alternative measures of university reputation attempted to capture the impact of the university's reputation on commercial outcomes from UIRCs (Sine et al., 2003). *Reputation Ranking* was an ordinal variable that ranked each university in order of their reputation. *Faculty Awards* was a continuous variable of the number of awards received per 1,000 faculty at each university in

2010. *Research Ranking* was an ordinal variable that ranked each university in order based on the dollar value of research grants received in 2010. The source of data for these variables was the Macleanǿs Magazine Reputational Survey of Canadian Universities in 2010.

Inventions Disclosures: Following the approach of many studies of commercialisation effectiveness (Thursby and Thursby, 2002, Friedman and Silberman, 2003), this was a continuous variable that measured the number of inventions disclosed to the university in 2010. The source of the data for this variable was the AUTM Canadian Licensing Activity Survey 2010.

TTO Staff: This was a continuous variable that measured the number of full-time employees of the university involved in technology transfer in 2010. This was similar to Gonzalez-Pernia et al.ǿs (2013) approach of using the total number of TTO staff as measured in full-time equivalencies (FTEs). The source of the data for this variable was the AUTM Canadian Licensing Activity Survey 2010.

TTO Experience: Following Ambos et al. (2008) and Gonzalez-Pernia et al. (2013), this was a continuous variable that measured the number of years since the universityǿs TTO was established. The variable captured the impact of technology transfer experience on UIRC commercialisation (Ambos et al., 2008, Lockett and Wright, 2005, O'Shea et al., 2005, Siegel et al., 2003). The source of the data for this variable was the AUTM Canadian Licensing Activity Survey 2010.

IP Ownership: This was a categorical variable that measured the IP ownership policy of the university in 2010. Prior research has found a relationship between IP policy and technology transfer (Lach and Schankerman, 2004, Siegel et al., 2004).

5.5.6: Excluded Variables

Several variables were considered for use in the model. However, some potentially important variables were excluded for the reasons discussed below.

Researcher Quality and Productivity: Previous studies have found a relationship between researcher quality and productivity, and commercialisation (Markman et al., 2008, Gulbrandsen and Smeby, 2005, Van Looy et al., 2004, Lach and Schankerman, 2004, Agrawal and Cockburn, 2003). Several U.S.-based studies have used the National Research Councilõs (NRC) *National Survey of Graduate Faculty.* Unfortunately, no comparable resource has been found that measures the quality of Canadian researchers.

Ambos et al. (2008) used the *ISI Web of Science* to count the citations of the researchersô prior publications as a proxy for scientific excellence. The same approach was attempted for this study. However, several hurdles were encountered in data collection from the *ISI Web of Science* database, including difficulty in locating researchers within the database, challenges in validating the identity of researchers in the case of similar and potentially duplicate entries, and complications in accurately determining the appropriate citations to include in the count. Data collection rules were developed in an attempt to mitigate these challenges, but they could not be applied consistently across all observations due to the structure of the database. Indeed, these and other limitations of the *ISI Web of Science* database have been noted in other studies (Leydesdorff, 2008, Meho, 2007, Yang and Meho, 2006). As a result, data collection on citation counts as a proxy for researcher quality was abandoned due to poor construct validity.

Based on the findings from the extant literature, it must be acknowledged that the absence of researcher productivity or quality measures created the potential for omitted variable bias in this studyø model. Econometric testing for omitted variable bias was conducted and is discussed in Section 6.5.

Firm Openness: Several prior studies have linked a firmø openness to their likelihood to collaborate and to their absorptive capacity. In the context of this study, the firmø likelihood to collaborate is not in question since the firms are by definition involved in a UIRC. Furthermore, alternative measures such as firm contribution and firm interaction, which measure the degree of the firmø involvement, have been included rather than the openness construct due to the availability of data.

5.6: Data Collection and Preparation

Considerable work was required in order to collect data from OCEø historical records and from other data sources, and to prepare it for statistical analysis. The primary consideration during the data collection phase was to obtain as large a sample as possible of complete and representative observations.

OCEø historical records were accessed on three distinct media: 1) an organisation-wide Management Information System (MIS); 2) various tracking spreadsheets kept by operating divisions; and 3) paper-based archives of project applications and other related documents.

Until approximately 2004, UIRC funding applications were submitted to OCE in paper form. These funding applications were then copied and distributed to expert reviewers as part of the evaluation process described in Section 3.3.3. Evaluation results and the management of the chosen UIRC projects were typically tracked using spreadsheets. Commercial outcomes from projects were tracked through an annual survey, the results of which were also tracked using spreadsheets. Beginning in approximately 2005, OCE began accepting funding applications in digital form. In parallel, the organisation began the implementation of a centralised MIS. Initially, the MIS was only used to capture data on new or current projects but its uptake varied among staff and divisions. A hybrid of the old tracking processes and the new MIS was used during a transitional period of several years. More recently, the MIS has been used extensively by staff to track leads, funding applications under development, application evaluations, management of active UIRC projects, and project outcomes. However, commercial outcomes from UIRC projects continued to be tracked annually using spreadsheets.

Given the context described above, the following data collection and preparation steps were undertaken:

> *Step 1 – Generate MIS Report:* The first step in data collection was to obtain a data report from OCE's MIS for all projects related to the UIRC programs described in Section 3.3.1. All of OCE's historical projects have been assigned a system number in the MIS. At the time of data collection for this study, the effort to populate the

MIS with historical data was still underway though largely complete. The MIS report obtained from OCE contained data on 837 observations.

Step 2 – Cross-Reference Historical Records: The second step involved cross-referencing the MIS data report with OCEõs historical UIRC project tracking spreadsheets. OCEõs paper-based archives were also referenced with the assistance of OCE staff. This step ensured that as many eligible observations as possible were included in the sample and helped to locate missing data in some observations. During this step, an additional 435 potential observations were examined. Data was obtained for 330 of these, increasing the total sample to 1,167 observations.

Step 3 – Apply Sampling Rules: The sample obtained from steps 1 and 2 included several observations of project applications that were either declined or withdrawn, and of projects that were either in development or currently active. Therefore, the sample was reduced to include only observations that met all of the following criteria:

a. Projects must have been supported through one of OCEõs research programs. These programs were designed primarily to support commercialisation from UIRC and were directly relevant to the research questions. Based on this criterion, 376 observations were removed from the sample.
b. Projects must have been selected for financial support by OCE. No incomplete, withdrawn or declined project applications were included as they did not meet OCEõs selection criteria. As a result, 56 additional observations were removed.

c. Projects must have included at least one firm as a contributor. The research questions address UIRC in particular, which by definition only included projects involving collaboration with industry. Therefore, only projects involving firms were relevant to the research questions. A total of 54 observations did not meet this criterion.

d. Projects must have been completed by March 31, 2009. This cut-off date provided a sufficient time lapse to allow project outcomes to have occurred and be recorded. The study data included project outcomes recorded until the last day of the data collection phase, March 31, 2012. No observations were removed since OCE provided no data on projects past this date.

e. Projects must have been completed as scheduled and not terminated early by OCE for any reason. Early termination of a project occurred infrequently and was typically the result of exceptional circumstances, such as the failure or inability of a collaborating firm to meet its obligations to the project or the illness of a researcher or student. No observations violated this criterion.

The application of the sampling rules reduced the size of the sample from 1,167 observations to 681 observations.

Step 4 – Link Project Outcomes: The sample was then cross-referenced with OCEôs commercial outcome spreadsheets. This involved linking individual licenses and startups to the UIRC project(s) from which they originated. In the majority of cases, the link between project and outcome was identified in the tracking spreadsheets. Nevertheless, great care was taken to ensure accuracy, since any error in or misrepresentation of commercialisation could compromise the integrity of the study's findings.

Step 5 – Sample Adjustments: The sample was adjusted to address unique occurrences within the data set. In the case where a single observation led to multiple commercial outcomes, the observation was duplicated to equal the number of outcomes. In the case where a single commercial outcome was the result of more than one observation, a successful outcome was recorded for each observation. These adjustments increased the size of the sample from 681 observations to 682 observations.

Step 6 – Adding Public Source Data: Data from public sources was obtained and recorded for each observation.

Step 7 - Data Preparation: The sample was recorded into a master database that included pre-coded fields for dependent and independent variables to ensure ease of access, manipulation and analysis of the data. A title code and a brief description were created for each variable, and the various sources of the data were logged. A unique identifier was assigned to each observation. The data were coded in a manner appropriate for the statistical tools that were used in the analysis. This included the creation of dummy variables to code qualitative data found in ordinal and categorical variables.

Step 8 - Data Verification: The data were verified for accuracy, to ensure quality of measurement, and to confirm that the data meets the assumptions of the statistical analysis to be undertaken (Sproull, 2002). This involved exploring the database in detail for completeness and to detect any errors created during the data collection process. 105 observations were identified as having potential errors or missing data. In these cases, the original archive documents in OCEǒs historical records were reviewed and the data were revised accordingly. Spelling differences in the names of certain researchers and firms were also standardised.

Ultimately, the data collection and preparation steps yielded a sample of 682 observations that include two dependent variable measures and 24 independent variable measures.

5.7: Missing Data

The data collection and sampling steps yielded a dataset that was robust and generally complete. Remaining cases of missing data were addressed as described below.

5.7.1: PhD Age

Exhaustive efforts were made to collect as much data as possible on *PhD Age* from OCEǒs historical records and public sources. Ultimately, 18 percent of the data for this variable was not available.

A number of alternatives for handling this missing data were considered, including:

- dropping the variable,
- deletion of observations with missing data,
- single imputation using means or regression estimates, and
- multiple imputation (MI).

MI was selected as the most robust estimation technique available. Rather than estimating a single value for each missing value, MI estimates a number of plausible values for each missing value. Each imputed value includes a random component that reflects the level of uncertainty around the true value. The dataset is analysed with standard procedures (in this case, using Discrete Choice Modeling) using each of the imputed values. The parameter estimates are then combined. This results in a statistical inference that reflects the uncertainty created by the missing values (Yuan, 2011).

MI procedures assume that the data were missing at random (MAR), meaning that the data were missing for reasons unrelated to the data itself, although it may be related to other observed data (Yuan, 2011). The data for *PhD Age* represented the number of years since a researcher earned a doctorate degree. It was obtained in part from OCE's historical records. In cases where it was not available in these records, it was obtained from public sources, such as the researcher's website or other publications. There was no evidence to suggest that the data on *PhD Age* was missing for any systematic reason related to the researcher's *PhD Age*. Therefore, the data satisfied the MAR assumption.

MI was applied using predictive mean matching, which preserved the existing distribution of the observed values since the normality of the underlying model was suspect (Little, 1988). Therefore, the imputed values fell within the range of values for *PhD Age* found within the dataset (0 to 44 years).

Following White et al. (2011), the number of *imputation*s used was equal to the percentage of cases with missing values. Since 18 percent of the data on *PhD Age* was missing, 18 imputations were used. The imputation model included all independent variables used in the analysis model to avoid any bias (White et al., 2011).

5.7.2: TTO Measures

The AUTM Canadian Licensing Activity Survey 2010 was the data source for three TTO measures: TTO Experience, TTO Staff and Invention Disclosures. However, six of the 18 universities in this study did not respond to the survey. To mitigate this, the missing data was obtained directly from each university in cooperation with OCEǿs field staff.

5.7.3: University Size

The Research Infosource ranking of Canadaǿs Top 50 Research Universities was used as the data source for the two measures of university size. One university in this study did not respond to the survey. In this case, comparable data was used from Macleanǿs Magazine 2010 Survey of Canadian Universities.

5.8: Descriptive Statistics

Descriptive statistics were used to summarise and describe the sample and measures used in this study. In particular, analysis of the distribution, central tendency and dispersion of the sample was conducted for each measure. The analysis revealed some non-normal data, including both heteroscedasticity and outliers. However, no corrective action was taken since the regression techniques used in this study make no assumption about the distribution of the independent variables (Agresti and Kateri, 2011).

5.8.1: Dependent Variables

Table 5.6 presents the descriptive statistics for the dependent variables, compared when possible to those from Ambos et al. (2008), the only other study found with commercialisation outcomes as a dependent variable and UIRCs as the unit of observation.

Table 5.6: Descriptive Statistics – Commercial Outcomes

Commercial Outcomes	N	Mean	Std. Dev.	Min	Max
Commercialisation	78	0.114	0.318	0	1
Commercial Outcomes by Type					
License	40	0.058	0.235	0	1
Startup	38	0.055	0.229	0	1

Commercialisation was achieved in 11.4 percent of observations (*n* = 78). When commercialisation was broken down by outcome type, 5.9 percent achieved a license (*n* = 40), while 5.6 percent achieved a startup (*n* = 38). Therefore, licenses and startups represented 51.3 percent and 48.7 percent of observations that achieved commercialisation, respectively. By comparison, 79 of the 207 UIRCs in Ambos et al.ꞌs (2008) sample generated a commercial outcome, a commercialisation rate of 38.2 percent. In their study, 19.3 percent (*n* = 40) of projects generated a startup and a patent or license, 15.9 percent (*n* = 33) generated only a patent or license, and 2.9 percent (*n* = 6) generated only a startup.

It would appear that the commercialisation success rate of UIRCs in this study is lower for some commercial outcomes compared to Ambos et al. (2008). The overall success rate in Ambos et al. (2008) is 19.3 percent, compared to 11.4 percent in this study. However, Ambos et al. (2008) included patents as commercial outcomes, while this study did not. Unfortunately, Ambos et al. (2008) did not identify what proportion of commercial outcomes were related only to patents. Their dichotomous dependent variable considered any of these forms of commercialisation as success. The only disambiguated dependent variable data provided by Ambos et al. (2008) is for startups. On this measure of commercialisation, their success rate was actually lower than that of this study (2.9%

compared to 5.8% percent, respectively). Therefore, it is not possible to directly compare whether the commercialisation success rate of this studyøs sample is truly lower than that of Ambos et al. (2008).

Indeed, the success rate of commercialisation can vary considerably based on a number of structural and contextual factors. For example, Gulbrandsen and Smeby (2005) asked 1967 tenured researchers in Norway whether any of their research activities had ever generated commercial outcomes. Patents were reported by 7 percent of researchers, while 10 percent reported ñcommercial productsò and 7 percent reported startup activity. Considering that Gulbrandsen and Smebyøs (2005) results include commercialisation over a researcherøs entire career, the success rate of their sample could be considered lower than that of this study.

Nevertheless, there may be a number of additional reasons for the differences in the commercialisation success rate of this study compared to Ambos et al. (2008). As described in Section 2.6, 89 percent of universities in Ontario have adopted inventor-owned intellectual property ownership policies (Hen, 2010). This system does not incentivise the disclosure of inventions and commercialisation outcomes, and an unknown proportion of the commercialisation outcomes from Canadian universities goes unreported. The commercialisation success rate of the UIRCs in this studyøs sample may be lower because they do not include biotechnology, which accounts for approximately 50 percent of university technology transfer activity (Mowery and Nelson, 2001). Ambos et al.øs (2008) sample was also focused in the fields of physical sciences and engineering, but included UIRCs in ñfundamentalò science, which may have included some life-sciences research.

5.8.2: Researcher Characteristics

Descriptive statistics for the researcher characteristics measured in this study are presented in Table 5.7.

Table 5.7: Descriptive Statistics – Researcher Characteristics

Researcher Characteristics	N	Mean	Std. Dev.	Min	Max
Hypothesis 1: Embeddedness:					
PhD Age (before MI applied)	558	14.302	9.104	0	44
Position					
Staff	19	0.027	0.164	0	1
Mid-Level	296	0.434	0.495	0	1
Full Professor	347	0.508	0.500	0	1
Distinguished	20	0.029	0.168	0	1
Control Variables:					
Researcher Interaction	682	0.589	1.116	0	9
Gender					
Male	605	0.887	0.316	0	1
Female	77	0.112	0.316	0	1

As described in Section 5.6.1, data on *PhD Age* was not available for 124 of the 682 observations in this study. Based on the *PhD Age* data collected (n = 558), the mean number of years since the researchers earned a doctoral-level degree was 14.3 years, while the maximum number of years since earning a doctoral-level degree was 44 years. The average time spent in academia for researchers in Ambos et al.ôs (2008) sample was 22.9 years.

With regard to *Position*, the vast majority of observations involved mid-career researchers as principal investigators, including assistant and associate professors (43.4 percent, n = 296), or full professors (50.8 percent, n = 347). Staff researchers, including post-doctoral fellows and adjunct professors, were principal investigators in 2.8 percent of the observations (n = 19), while distinguished professors were principal investigators in 2.9 percent of the observations (n = 20). Similarly, 66 percent of researchers were full professors in Ambos et al.ôs (2008) sample.

Although the maximum number of OCE-funded UIRCs in which a researcher was previously involved was nine, the average number was considerably lower (□ = 0.6 previous UIRCs). In fact, 66.4 percent (n = 453) of observations involved researchers with no previous interaction with firms in OCE-funded UIRCs. In comparison, the average number of previous funding agency projects received by researchers in Ambos et al.ôs (2008) sample was 5.6 projects, although it should be noted these were not necessarily UIRCs. With regard to gender, 11.3 percent of observations in the study involved female researchers.

5.8.3: Firm Characteristics

Table 5.8 presents the descriptive statistics for the studyôs measures of firm characteristics.

Table 5.8: Descriptive Statistics – Firm Characteristics

Firm Characteristics	N	Mean	Std. Dev.	Min	Max
Hypothesis 2: Firm Contribution					
Firm Cash	682	41855	84328	0	1010500
Firm In-Kind	682	69826	114096	0	1313240
Control Variables:					
Firm Size					
Micro	169	0.247	0.432	0	1
Small	219	0.321	0.467	0	1
Medium	181	0.265	0.441	0	1
Large	113	0.165	0.372	0	1
Firm Interaction	682	0.519	1.459	0	13
Number of Firms	682	1.378	1.186	1	14

UIRCs in this study were led by firms in a range of sizes. Observations most frequently involved small firms (*n* = 219) followed by medium-sized firms (*n* = 181), which together represented 58.7 percent of observations. Small firms represented an even larger proportion (70.4 percent) of Garcia-Aracil and De Lucioꞔs (2008) sample of Valencian firms engaged in UIRCs.

Firms contributed an average of $41,856 in cash and $69,827 in-kind to UIRCs in this study. However, the variance in cash and in-kind contribution in the sample is notable (*s* = $84,329 and *s* = $114,096, respectively). Several observations involved either no cash contribution (10.8 percent, *n* =74) or no in-kind contribution (7.8 percent, *n* = 53) on the part of the firm(s). Only 73 percent of UIRCs in Ambos et al.ꞔs (2008) sample received a contribution from a firm.

The maximum number of OCE-supported UIRCs in which a firm in the sample was previously involved is 13. However, the average number was considerably lower (⍰ = 0.5 previous UIRCs). In fact, 76.4 percent (n = 521) of observations involved firms with no previous interaction in UIRCs. Although the largest number of firms involved in a UIRC in this sample is 14, observations most frequently involved one firm (82.7 percent, *n* = 564).

5.8.4: Project Characteristics

Table 5.8 presents the descriptive statistics for the UIRC project characteristics.

Table 5.9: Descriptive Statistics – Project Characteristics

Project Characteristics	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Hypothesis 3: Industry Sector					
Research Field					
Communications and Info. Tech. (CIT)	124	0.181	0.385	0	1
Materials and Manufacturing (MM)	380	0.557	0.497	0	1
Earth and Environment (EET)	153	0.224	0.417	0	1
Photonics	25	0.036	0.188	0	1
Control Variables:					
Research Stage					
Earliest	372	0.545	0.498	0	1
Mid-stage	267	0.391	0.488	0	1
Latest	43	0.063	0.243	0	1
Funding	682	90909	100299	2450	800000
Length	682	17.38	11.48	1	55
Distance	682	231.45	667.10	0	7281

The *Field of Research* for the majority of observations was materials and manufacturing (55.7 percent, *n* = 380) followed by earth and environmental technologies

(22.4 percent, *n* = 153) and communications and information technologies (18.2 percent, *n* = 124). The field of photonics represented only 3.7 percent of observations (*n* = 25).

With regard to stage, the majority of the observations represented mid-stage UIRCs (54.5 percent, *n* = 372). Late-stage UIRCs represented 39.1 percent of observations (*n* = 267), while later-stage proof-of-concept UIRCs represented only 6.3 percent of observations (*n* = 43).

UIRCs in the sample received an average of $90,909 in *Funding* from OCE and had an average *Duration* of just over 17 months. The average project size in Ambos et al.ôs (2008) sample was £222,000, compared to $202,589 in the sample for this study (including OCE funding, and firm cash and in-kind).

The average *Distance* between the researcher and the firm was 231 kilometres, although the distance ranged considerably; some collaborators were co-located within the same facility, while others were over 7,000 kilometres away. Fifty percent of the collaborators were within 73.3 kilometres of each other.

5.8.5: University Characteristics

The descriptive statistics for the measures of university characteristics used in this study are presented in Table 5.10.

Table 5.10: Descriptive Statistics – University Characteristics

University Characteristics	N	Mean	Std. Dev.	Min	Max
Controls of University Size:					
Research Capacity	682	309637	302905	1693	878725
University Faculty	682	1285	654	96	2439
University Operations	682	10554	1739	8323	14643
Controls of University Reputation:					
Reputation Ranking	682	5.391	4.482	1	18
Faculty Awards	682	5.392	3.126	0	10.8
Research Ranking	682	6.897	4.737	1	18
Controls of TTO:					
Invention Disclosures	682	62.860	45.366	0	136
TTO Experience	682	18.533	8.003	0	29
TTO Staff	682	7.723	5.215	0	15.5
IP Ownership					
University	106	0.155	0.362	0	1
Creator	576	0.844	0.362	0	1

The sample involved 18 universities across Ontario, whose expenditures on research and development and total number of faculty members illustrated the notable differences in scale among the institutions. The largest university (based on both measures of size) was involved in 18.9 percent of the observations (n = 129), and was also the top performer on all three measures of technology transfer office operations; its technology transfer office has been in operation for 29 years, employed 15.5 staff and received 136 invention disclosures per year. The average *TTO Experience* in Ambos et al.õs (2008) sample was 12.8 years, compared to 18.5 years in the sample for this study. In U.S.

universities in 2007, the number of TTO staff ranged from 0 to 77 full-time employees (x = 6.4), while the number of invention disclosures ranged from 4 to 1,411 (x = 130.5).[32]

Two different university rankings were used to measure reputation (*Reputation Ranking* and *Research Ranking*). A third measure showed that the number of awards received per 1,000 faculty members ranged from 0 to 10.8. Sixteen of 18 universities had creator-owned policies, which represented 84.5 percent of the observations in this sample.

5.9: Chapter Summary

The study employed a correlational research design that is appropriate to address the research questions, and to test the hypotheses regarding the relationships between the factors that lead to commercialisation from UIRCs. The unit of observation for the study was the UIRC, and data were collected for two dependent variables and 24 independent variables on a sample of 682 UIRCs selected for funding by OCE using a formalised evaluation process. Data was sourced from OCEõs historical records and supplemented by data from other public sources. Appropriate strategies were employed to address missing data in three independent variables. Descriptive statistics were provided to explore the distribution, central tendency and dispersion of the sample, in preparation for the statistical analysis described in the next chapter.

[32] AUTM U.S. Licensing Activity Survey: Fiscal Year 2007

CHAPTER VI: ANALYSIS

Following the methodology described in Chapter V, this chapter defines the modeling techniques that were used, describes the data analysis steps that were undertaken, and presents the final specification of the model. The interpretation of the results will be discussed in Chapter VII: Results.

6.1: Introduction

Section 6.2 describes the Binomial Logit (BNL) and Multinomial Logit (MNL) models used, and why they are appropriate for the research questions and data collected for the study.

Section 6.3 illustrates how the most parsimonious BNL and MNL models were fitted over four distinct steps.

Section 6.4 describes the results of the first step, which attempted to address multicollinearity between variables or groups of variables using correlation matrices, bivariate regressions and the variance inflation factor.

Section 6.5 describes the results of the second step, in which multivariate and fixed-effects regressions were used to assess how the data fit the BNL and MNL models.

Section 6.6 describes the results of the third step, involving further analysis of independent variables that were near or just below the threshold for statistical significance.

Section 6.7 describes the results of the fourth step, which used Likelihood Ratio and Goodness-of-Fit tests to determine the most parsimonious models possible.

6.2: Model Description

The study made use of Discrete Choice Modeling (DCM) techniques to test the hypotheses. The goal of DCM is to understand the factors that are collectively associated with a given choice (Train, 2003). Some of these factors may be observed by the researcher while others are not. Since some of the factors are not observed, DCM is not deterministic and cannot predict a given choice exactly. Rather, the DCM derives the probability of any particular choice based on the observed factors, assuming the unobserved factors are random in nature.

DCM includes a number of models that are appropriate for different types of data and that rely on different assumptions. Binomial logit (BNL) and multinomial logit (MNL) are the most appropriate models for this study because they are used to determine the predictive capacity of a number of independent variables over either a binary dependent variable or a polychotomous categorical dependent variable, respectively. The study met two other important criteria for the application of MNL. First, the dependent variable represented unordered choices that were mutually exclusive, exhaustive, and finite in number (Train, 2003). Second, the unobserved factors in the model were uncorrelated over the choices, and had the same variance for all choices, known as the assumption of Independence of Irrelevant Alternatives (IIA) (Train, 2003). In practical terms, IIA measures how closely related the choices are. For the purposes of this study, it was reasonable to assume that the measures of UIRC commercialisation, licenses and startups, were independent outcomes, each of which may be more attractive to some stakeholders than to others. The assumption was tested using the Hausman specification test (Hausman and McFadden, 1984). The test results, which are presented below in Table 4.1, offer no evidence that the IIA assumption has been violated.

Table 6.1: Suest-based Hausman Test of IIA assumption

Omitted	chi2	df	P>chi2	Evidence
License	13.814	24	0.951	for Ho
Startup	8.353	24	0.999	for Ho

Ho: Odds (Outcome-J vs Outcome-K) are independent of other alternatives

A detailed specification of the BNL and the MNL models is presented below.

6.2.1: Binomial Logit Model

The BNL model was specified as follows:

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

where

$F(x)$ = probability of commercialisation

x = the selected set of independent variables

6.2.2: Multinomial Logit Model

The MNL model was specified as follows:

$$P_{license} = \frac{e^{\beta_{license} X_i}}{1 + e^{\beta_{license} X_i} + e^{\beta_{startup} X_i}}$$

$$P_{startup} = \frac{e^{\beta_{startup} X_i}}{1 + e^{\beta_{license} X_i} + e^{\beta_{startup} X_i}}$$

$$P_{failure} = \frac{1}{1 + e^{\beta_{license} X_i} + e^{\beta_{startup} X_i}}$$

where

failure = reference choice

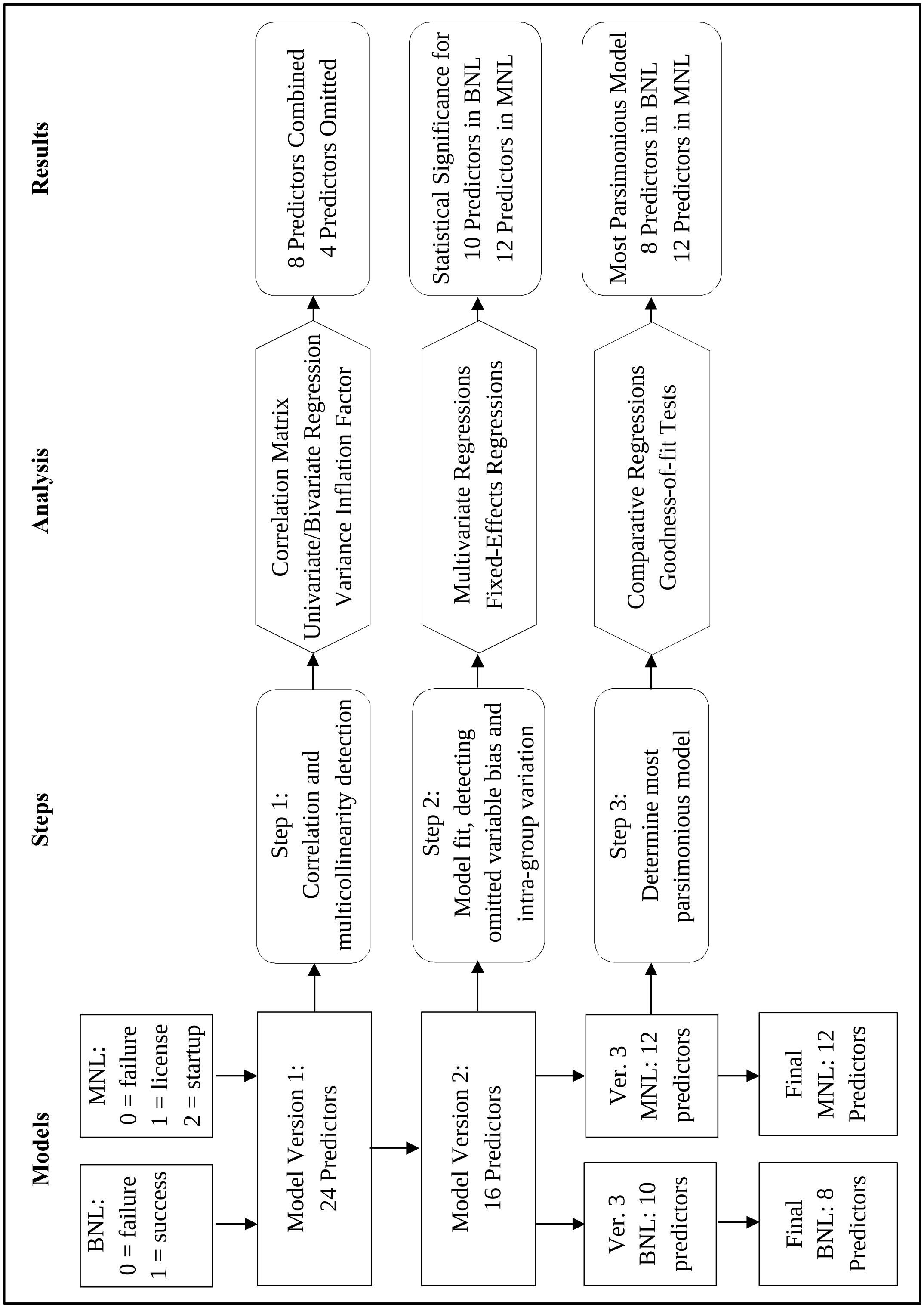
X_i = the selected set of independent variables

$1 = P_{license} + P_{startup} + P_{failure}$

6.3: Model Specification

Given the large number of control variables included in the models, considerable care was given to determining the nature of the relationships between the variables and which independent variables should be retained to yield the most parsimonious model possible. As a result, the model was specified in multiple steps. Figure 4.1 summarises the purpose of each step, the analysis undertaken, and the resulting evolution of the model from one step to the next.

Fig. 6.1: Model Specification



The BNL model was fit using the binary dependent variable *Commercialisation,* 5 independent variables related to the three hypotheses to be tested, and 19 control variables. The MNL model was fit using the polychotomous categorical dependent variable *Commercial Outcomes by Type* and the same independent variables to test the three hypotheses.

As described above, *Version 1* of the model included a total of 24 independent variables. The model was analysed using a correlation matrix, bivariate regressions and the Variance Inflation Factor (VIF) to reveal correlations and address potential multicollinearity. As a result of this analysis, eight independent variables were combined into four new variables and four other independent variables were omitted.

Version 2 of the model included the 16 remaining or combined independent variables. The model was analysed using multivariate BNL, university and researcher fixed-effects, and MNL regressions to assess the model fit, and to detect any potential omitted variable bias or intra-group variation. As a result, 10 independent variables were found to be statistically significant or near significant in the BNL model, and 12 independent variables were found to be statistically significant or near significant in the MNL model.

Version 3 included the remaining 10 and 12 independent variables in the BNL and MNL models, respectively. The models were analysed using Likelihood Ratio tests and several goodness-of-fit tests to determine the most parsimonious models possible. As a result of this step, the final BNL and MNL models included eight and 12 independent variables, respectively.

The following sections provide a detailed description of the analysis conducted at each step.

6.4: Step 1 - Correlation and Multicollinearity Detection

Version 1 of the model specification included 24 independent variables:

Table 6.2: Independent Variables in Model Version 1

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • PhD Age • Position *Control Variables:* • Interaction • Gender	*Hypothesis 2:* • Firm Cash • Firm In-kind *Control Variables:* • Firm Size • Interaction • Number of Firms	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding • Length • Distance	*University Size Controls:* • Research Capacity • Faculty • Operations *Reputation Controls:* • Reputation Ranking • Research Ranking • Faculty Awards *TTO Controls:* • Invention Disclosures • TTO Staff • TTO Experience • IP Ownership

6.4.1: Analysis of Model Version 1

A number of statistical analyses were conducted on *Version 1* of the model with the goal of understanding the relationships between the variables and detecting any possible multicollinearity. First, correlation matrices were created, and the correlation coefficients were used to explore relationships between variables or groups of variables. The correlation matrix including all 24 independent variables can be found in Appendix B. Correlation matrices for each category of independent variable (researcher, firm, university and project characteristics) were also created and are discussed in the following sections. Then, univariate and bivariate regressions were analysed using the Wald test to assess the significance of each independent variable as a predictor and to explore the relationship between each pair of independent variables.

Although the correlation matrix and bivariate regressions were useful in identifying relationships between pairs of variables, they may not reveal latent multivariate relationships, or relationships between groups of variables, that could also be a source of multicollinearity. Therefore, the model was tested by computing the tolerance and the Variance Inflation Factor (VIF) for each independent variable. The tolerance and VIF are widely used tests of multicollinearity that describe how much the variance of the estimated coefficients are inflated due to correlation between predictors (O'Brien, 2007).

The analysis identified multicollinearity among several of the predictors due to the large number of predictors in the model, the inherent relationship between the characteristics of UIRC stakeholders, and the fact that several predictors were alternative measures of the same characteristics. In cases where multicollinearity was detected, two remedies were considered:

1. *Combining or scaling variables:* Used in cases where correlated variables, including variables that are alternative measures of the same characteristics, could be brought together in some type of logical or useful way; or

2. *Omitting variables:* Used to choose among alternative measures of the same characteristic or in cases where the independent impact of the characteristic could not be isolated.

The results of this analysis and the remedies applied are described below.

6.4.2: Multicollinearity within Researcher Characteristics

Table 6.3 shows the correlation matrix for the researcher embeddedness variables and the researcher control variables:

Table 6.3: Correlation Matrix for Researcher Characteristics

	Commercial-isation	PhD Age	Position				Firm Inter.	Gender	
			Staff	Mid	Full	Dist.		Male	Female
Commercialisation	1.00								
PhD Age	0.15	1.00							
Staff	-0.03	-0.11	1.00						
Mid-level	-0.16	-0.52	-0.14	1.00					
Full Professor	0.16	0.44	-0.17	-0.90	1.00				
Distinguished	0.03	0.36	-0.03	-0.14	-0.17	1.00			
Firm Interaction	0.03	0.09	-0.03	-0.01	0.03	-0.03	1.00		
Male	0.11	0.13	0.05	-0.08	0.04	0.06	0.11	1.00	
Female	-0.11	-0.13	-0.05	0.08	-0.04	-0.06	-0.11	-1.00	1.00

With regard to the variables necessary to test Hypothesis 1, *PhD Age* and *Position* were moderately correlated (r = .59). In univariate BNL regressions with *PhD Age* and *Position* as the only independent variable in each regression, *PhD Age* and the *Position* category *Full Professor* were positive and significant at the one percent level. However, *PhD Age* fell below significance at the five percent level in a bivariate BNL regression where both *PhD Age* and *Position* were included as the two independent variables. These regression results are included for reference in Appendix C.

As discussed earlier, Ambos et al. (2008) contended that a researcherõs ñEmbeddednessò should be measured using ñboth the academic position of the principal investigator [*Position*], as well as the length of time they have spent with pursuing academic interests [*PhD Age*]ò. Their results were consistent with those of earlier studies that ñsuggested an interesting split between younger, more entrepreneurial ónew-schoolô faculty and older, more traditional óold-schoolô facultyò (Ambos et al., 2008, Owen-Smith and Powell, 2001b), and the emergence of ñstar scientistsò (Zucker and Darby, 2001).

As a solution to the collinearity problem identified in this study, Ambos et al.õs (2008) concept of *Embeddedness* was operationalised into a new categorical variable by applying the following interaction technique:

Table 6.4: *Embeddedness* Interaction Technique

Embeddedness =		***PhD Age***	
		=> 14 yrs.	**15+ yrs**
Position	**Mid-Level**	*New School*	*Laggards*
	Full	*Rising Stars*	*Old School*

The result of the interaction technique was four new categories of researchers of diverse levels of academic embeddedness. Researchers with the *Position* of *Staff* and *Distinguished* were not included in the interaction technique. Rather, these categories were then added to *Embeddedness* to create a 6-category variable. Fourteen years was used as cutoff between the categories because it approximately represented the mean *PhD Age* ($\bar{x}$ = 14.3).

6.4.3: Multicollinearity within Firm Characteristics

Table 6.5 shows the correlation matrix for the measures of firm contribution and the firm control variables:

Table 6.5: Correlation Matrix for Firm Characteristics

	TT Overall	Firm Size				Cash	In Kind	Firm Inter.	# Firms
		Micro	Small	Medium	Large				
TT Overall	1.00								
Micro	0.00	1.00							
Small	-0.02	-0.39	1.00						
Medium	-0.01	-0.35	-0.41	1.00					
Large	0.04	-0.26	-0.31	-0.27	1.00				
Firm Cash	0.12	-0.07	-0.06	0.10	0.04	1.00			
Firm In kind	0.17	0.00	0.01	0.04	-0.05	0.38	1.00		
Firm Interaction	0.07	-0.15	-0.12	0.27	0.00	0.09	-0.03	1.00	
# of Firms	0.04	0.04	0.00	-0.03	-0.01	0.33	0.26	-0.06	1.00

With regard to the variables necessary to test Hypothesis 2, the measures of a firmôs contribution to a UIRC, *Firm Cash* and *Firm In-kind*, were correlated with the measure of OCEôs contribution, *Funding* (r =.55, r = .51).[33] Therefore, the new scale variables *Firm Cash Ratio* and *Firm In-kind Ratio* were created by dividing *Firm Cash* and *Firm In-kind* by *Funding*. The new variables represent the ratio of the firmôs contribution to the UIRC

[33] These correlations can be found in the correlation matrix of all variables found in Appendix B.

compared to that of OCE. Testing the hypothesis by using the amount of a firmôs contribution relative to the government subsidy provided by OCE is consistent with the concept of ñcrowding-inò found in the extant literature, and measures the additionality created by government subsidies for research.

6.4.4: Multicollinearity within Project Characteristics

Table 6.6 shows the correlation matrix for the industry sector of the project, and for the project control variables:

Table 6.6: Correlation Matrix for Project Characteristics

	TT Overall	Research Field				Research Stage			Fund.	Lgth.	Dist.
		CIT	MM	EET	Pho.	Earliest	Mid	Latest			
TT Overall	1.00										
CIT	0.14	1.00									
MM	-0.02	-0.53	1.00								
EET	-0.14	-0.25	-0.60	1.00							
Photonics	0.08	-0.09	-0.22	-0.10	1.00						
Earliest	0.20	0.28	-0.32	0.17	-0.09	1.00					
Mid	-0.18	-0.24	0.29	-0.17	0.10	-0.88	1.00				
Latest	-0.04	-0.09	0.07	0.01	-0.02	-0.28	-0.21	1.00			
Funding	0.22	0.41	-0.37	0.09	-0.06	0.63	-0.63	-0.03	1.00		
Length	0.11	0.16	-0.26	0.22	-0.14	0.77	-0.80	0.04	0.62	1.00	
Distance	-0.06	-0.04	-0.04	0.10	-0.03	0.08	-0.08	0.01	0.04	0.04	1.00

No correlation or multicollinearity issues were detected for the variables necessary to test Hypothesis 3. However, some correlations were detected among the project control variables. The measures of a UIRCôs budget size and length were correlated (r = .62), a simple reflection that longer UIRCs tend to have larger budgets. Consequently, the new variable *Funding per Month* was created by dividing *Funding* by *Length*. The new variable represents OCEôs contribution to a UIRC per month.

As a result of the analysis described above, *Version 1* of the model was reduced from 24 to 16 independent variables.

6.4.5: Multicollinearity within University Characteristics

Table 6.7 shows the correlation matrix for university control variables:

Table 6.7: Correlation Matrix for University Characteristics

	TT Overall	Cap.	Faculty	Ops.	Rep. Rank	Award	Res. Rank	Inv.	TTO Exp.	TTO Staff	IP Ownership	
											Uni.	Creator
TT Overall	1.00											
Research Capacity	0.16	1.00										
# Faculty	0.14	0.96	1.00									
Operations	-0.08	0.02	-0.08	1.00								
Reputation	-0.10	-0.54	-0.55	0.28	1.00							
Awards	0.13	0.73	0.66	0.17	-0.61	1.00						
Research Rank	-0.12	-0.59	-0.56	0.15	0.54	-0.83	1.00					
Inventions	0.12	0.84	0.80	0.09	-0.60	0.76	-0.67	1.00				
TTO Experience	0.16	0.79	0.72	-0.07	-0.73	0.88	-0.73	0.85	1.00			
TTO Staff	0.11	0.89	0.87	0.09	-0.75	0.82	-0.69	0.88	0.85	1.00		
University	0.02	0.16	0.17	-0.01	-0.10	0.04	0.19	-0.06	0.19	0.15	1.00	
Creator	-0.02	-0.16	-0.17	0.01	0.10	-0.04	-0.19	0.06	-0.19	-0.15	-1.00	1.00

Three alternative measures of university size were included in the model. The measures *Research Capacity* and *University Faculty* were highly correlated ($r = 0.96$), but neither was correlated with *University Operations* ($r = 0.02$, $r = -0.08$). Therefore, the new variable *Research per Faculty* was created by dividing *Research Capacity* by *University*

Faculty. The new variable measures the university’s expenditures on research and development per faculty member.

Three measures of a university’s technology transfer office were included in the model. *Invention Disclosures, TTO Staff* and *TTO Experience* were all correlated with each other. The new scale variable *Inventions per TTO Staff* was created by dividing *Invention Disclosures* by *TTO Staff*. The new variable measures the number of inventions disclosed to the university per full-time employee involved in technology transfer.

Three alternative measures of university reputation were included in the initial model: *Reputation Ranking*, *Faculty Awards* and *Research Ranking*. Predictably, all combinations of these measures were found to be correlated with each other in the correlation matrix.

As described above, the collinearity found between various university characteristics was largely addressed by combining or scaling the variables. The exceptions were *TTO Experience*, the third alternative measure of a university’s technology transfer office, and the three alternative reputation measures, which could not easily be scaled. Therefore, the Variance Inflation Factor (VIF) was used to measure the extent of the multicollinearity caused by these predictors. Table 6.8 compares the tolerance and VIFs of two models - one that included all independent variables (including the four new variables described in this section), and one that omitted the variables *Reputation Ranking* and *TTO Experience*.

Table 6.8: Tolerance and Variance Inflation Factor

	Variables Included			Variables Omitted		
	VIF	**Tolerance**	**R2**	**VIF**	**Tolerance**	**R2**
Researcher Characteristics:						
Embeddedness						
Staff	1.16	0.8608	0.1392	1.16	0.8637	0.1363
Rising Stars	1.31	0.7606	0.2394	1.31	0.764	0.236
Old School	1.51	0.6609	0.3391	1.51	0.6611	0.3389
Laggards	1.23	0.8115	0.1885	1.23	0.8131	0.1869
Distinguished	1.12	0.8944	0.1056	1.12	0.8961	0.1039
Firm Interaction	1.2	0.8299	0.1701	1.2	0.8305	0.1695
Gender	1.09	0.921	0.079	1.08	0.9247	0.0753
Firm Characteristics:						
Firm Size						
Micro	1.4	0.715	0.285	1.4	0.7155	0.2845
Medium	1.57	0.6365	0.3635	1.56	0.6418	0.3582
Large	1.36	0.7371	0.2629	1.34	0.7453	0.2547
Firm Cash Ratio	1.15	0.8674	0.1326	1.14	0.8742	0.1258
Firm In-kind Ratio	1.16	0.8655	0.1345	1.15	0.8659	0.1341
Number of Firms	1.27	0.7867	0.2133	1.27	0.7872	0.2128
Firm Interaction	1.2	0.8299	0.1701	1.2	0.8305	0.1695
University Characteristics:						
Research per Faculty	10.44	0.0958	0.9042	1.42	0.7024	0.2976
Uni. Operations	1.79	0.5592	0.4408	1.14	0.8756	0.1244
Reputation Ranking	4.32	0.2312	0.7688	omitted		
Inventions per TTO Staff	2.22	0.4507	0.5493	1.3	0.7703	0.2297
TTO Experience	11.69	0.0855	0.9145	omitted		
IP Ownership	1.38	0.7242	0.2758	1.21	0.825	0.175
Project Characteristics:						
Research Field						
CIT	1.94	0.5158	0.4842	1.92	0.5199	0.4801
MM	1.91	0.5228	0.4772	1.89	0.5297	0.4703
Photonics	1.28	0.7838	0.2162	1.26	0.7941	0.2059
Research Stage						
Earliest	1.62	0.6184	0.3816	1.61	0.621	0.379
Latest	1.2	0.8335	0.1665	1.2	0.8348	0.1652
Funding per Month	1.57	0.6369	0.3631	1.57	0.6375	0.3625
Distance	1.06	0.9434	0.0566	1.06	0.9467	0.0533
Mean VIF	**2.22**			**1.33**		

The VIF and tolerance statistics indicated the presence of a latent but strong relationship between *TTO Experience* and *Research per Faculty* (VIF = 11.69 and VIF = 10.44, respectively). Consequently, the variable *TTO Experience* was omitted from the model.

The VIF and tolerance statistics also indicated multicollinearity with *Reputation Ranking* (VIF = 4.32, Tolerance = 0.23). The results were similar when using *Faculty Awards* or *Research Ranking* as alternative measures of university reputation in the comparative VIF models. The independent impact of university reputation on UIRC *Commercialisation* could not be isolated and as a result, the decision was made to omit *Reputation Ranking*, *Faculty Awards* and *Research Ranking* from the model.

6.5: Step 2 - Fitting the Model

Version 2 of the model included the 16 remaining independent variables: three variables used to test the hypotheses, and 13 control variables.

Table 6.9: Independent Variables in Model Version 2

Researcher Characteristics	**Firm Characteristics**	**Project Characteristics**	**University Characteristics**
Hypothesis 1: • Embeddedness *Control Variables:* • Interaction • Gender	*Hypothesis 2:* • Firm Cash Ratio • Firm In-kind Ratio *Control Variables:* • Firm Size • Interaction • Number of Firms	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding per Month • Distance	*Control Variables:* • Research per Faculty • Operations • Invention per TTO Staff • IP Ownership

6.5.1: Omitted Variable Bias

Omitted variable bias is a consequence of omitting a potentially relevant independent variable from a model, causing the coefficients of the remaining variables to be over or under-estimated (Kennedy, 1992). It is impossible to include all the relevant variables in an econometric specification, since there may always be factors influencing behaviour that have not yet been observed by researchers or explained by existing theory. Therefore, omitted variable bias in econometric studies is unavoidable (Clarke, 2005). Kennedy (1992) stated: ñUnfortunately there are no unequivocal means of testing for whether an unknown explanatory variable has been omittedò. Especially in studies such as this one that involve individual characteristics, some important factors may be operationally unobservable. For example, there is no definitive way to include a researcherøs innate ability or motivation in the model. Previous studies in related fields of research have included various measures of researcher publication productivity and quality as proxies. These proxies are problematic for the reasons described in Section 5.5.6. Some previous studies have indeed found researcher productivity and quality to be associated with university technology transfer (Markman et al., 2008, Lach and Schankerman, 2004). However, other studies have found no such relationship; this included Ambos et al. (2008), which is the only previous study found to specifically investigate the factors associated with commercialisation from UIRCs.

Nevertheless, it would have been ideal to include measures of researcher productivity and quality in this studyøs model. As described in Section 5.6.6, reliable data for these measures was not available. Regrettably, the effect of omitting researcher productivity and quality on the parameter estimates of the remaining variables cannot be known:

> ñThe only thing that can be said for certain is that unless we find ourselves in the precise situation described by textbooks, we cannot know the effect of including an additional relevant variable on the bias of a coefficient of interest. The addition may increase or decrease the bias, and we cannot know for sure which is the case in any particular situation.ò (Clarke, 2005)

In the absence of a definitive test to measure the bias created by omitting a potentially relevant variable, fixed-effects regressions can remove omitted variable bias by adjusting for intra-group variation that is not explained by the independent variables. Therefore, in addition to the regular BNL regression, two fixed-effect BNL regressions were attempted. The first fixed-effects regression sought to identify any unexplained variation within multiple UIRC projects that involved the same researcher, consequently removing any bias resulting from the omission of researcher productivity and quality, and of any other relevant researcher characteristics that may be unobserved.

The 682 UIRCs under observation in this study involved 454 individual researchers, which were interpreted in the fixed-effects regression as 454 ñgroupsò. Among them, 135 researchers were involved in more than one of the UIRCs in this sample. Eight researchers were involved in more than five of the UIRCs in this sample. Unfortunately, the results of the researcher fixed-effects regression were problematic. Of the 454 groups, 430 groups were automatically dropped from the regression because they had all positive or all negative commercial outcomes. Therefore, the regression was conducted using only 24 groups that collectively represented only 78 of the 682 observations available. In addition, five independent variables were automatically omitted from the regression (*Research per*

Faculty, *University Operations*, *Inventions per TTO Staff*, *Research Field,* and *IP Ownership*) because there was no within-group variance in the remaining data for these variables. As a result, the fixed-effect regression for researchers was not effective in removing bias created by the omission of potentially relevant researcher variables.

Some of the variables that were included in the model were likely to be highly correlated with researcher productivity and quality, which may serve as a mitigating factor. It would be reasonable to assume that researchers who produced more high quality publications would be more likely to advance in their academic careers, leading to greater *Embeddedness* (Gulbrandsen and Smeby, 2005). In addition, the descriptive statistics presented in Section 6.4 showed a correlation between a universityǿs reputation and its research capacity as measured by *Research per Faculty*. It would be reasonable to assume that more productive and higher quality researchers would be attracted to universities with a better reputation and higher research capacity, suggesting a correlation between researcher productivity and quality, and *Research per Faculty*. Despite the various attempts to limit the risk of omitted variable bias, it remains a limitation of this study.

The second fixed-effects regression attempted to adjust for the fixed-effects of each university. As described in Section 6.4.4, the data on university characteristics varied considerably across institutions but not over time. Specific individual differences that were unobserved may have existed within each university, potentially biasing the results. The goal of the university fixed-effects regression was to identify any variation within universities in an effort to remove omitted variable bias. The regular BNL estimates were compared to those of the BNL adjusted for the fixed-effects of the university. As described in detail below, the results of the university fixed-effects model did not differ significantly from the regular BNL model, with the exception of the variable *Gender*.

6.5.2: Analysis of Model Version 2

BNL and MNL regressions were performed on *Version 2* of the model. The parameter estimates were assessed to determine the sign and statistical significance of each independent variable. The estimates were analysed using the Wald test to assess the contribution made by each independent variable to the overall fit of the model.

The complete BNL, university fixed-effects, and MNL model regression results can be found in Appendix D. A summary of the regression results is provided below in Tables 6.10 through 6.13. These regression results include the three independent variables used to test the hypotheses, and the 13 control variables. The results are displayed and discussed by category (i.e. researcher, firm, university and project characteristics) for the benefit of the reader. In each table:

Column (1) = BNL estimates

Column (2) = BNL adjusted for the fixed-effects of the university

Column (3) = MNL estimates for Licenses

Column (4) = MNL estimates for Startups

In this step, only the sign and statistical significance level of each variable was analysed to identify those that should remain in the model. The results of the hypothesis tests and marginal effects for each of the remaining variables in the model are discussed in the next chapter.

6.5.3: Test of Hypothesis 1 - Embeddedness

Hypothesis 1 was as follows:

> **Hypothesis 1: UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.**

The hypothesis was tested using the categorical variable *Embeddedness*, which represented a researcherȏs level of embeddedness within academia based on their position and the number of years since they earned a PhD. The estimated test results for Hypothesis 1 are reported in Table 6.10.

Table 6.10: BNL and MNL Regression Results for Researcher Characteristics

Researcher Characteristics	BNL Depvar = Commercialisation				MNL Depvar = Outcomes by Type			
			Fixed-Effects		License		Startup	
Hypothesis 1:								
Embeddedness [New School}								
Staff	-0.206	-(0.17)	-0.274	-(0.23)	omitted		omitted	
Rising Stars	0.815*	(1.68)	0.864*	(1.75)	0.850	(1.25)	1.000	(1.51)
Old School	1.109***	(2.81)	1.142***	(2.88)	1.522***	(2.86)	1.154**	(2.07)
Laggards	0.916	(1.57)	0.945	(1.58)	-0.134	-(0.14)	1.559**	(2.14)
Distinguished	0.942	(1.17)	0.781	(0.95)	1.589	(1.54)	0.728	(0.59)
Control Variables:								
Researcher Interaction	0.090	(0.77)	0.062	(0.54)	-0.146	-(0.66)	0.257*	(1.90)
Gender [Male]								
Female	-1.571**	-(2.03)	-1.472*	-(1.87)	omitted		omitted	

Z-Scores in (parentheses)   Reference categories in [brackets]
Significant at the * 0.1 level; ** 0.05; * 0.01**

The sign and significance levels of the categorical variable *Embeddedness* were interpreted relative to the omitted reference category *New School*. The estimated coefficients for *Staff* were negative but not significant for *Commercialisation*. The category *Staff* was omitted from the MNL model because the number of *Startup* outcomes in this sample for this category was zero, leading to perfect prediction and causing potential instabilities in maximisation. As a result, 19 observations were excluded from the MNL regression.

The estimated coefficient for *Old School* was significant and positive. *Old School* was positively related to *Commercialisation,* and with both the outcomes *License* and *Startup* specifically. The estimated coefficient for *Rising Stars* was significant and positive for *Commercialisation*, but not significant for a *License* or *Startup* specifically. The estimated coefficient for *Laggards* was positive but slightly below the threshold for significance at the 10 percent level for *Commercialisation*. However, the relationship between *Laggards* and a *Startup* was positive and significant but was not significant for a *License*. The estimated coefficients for *Distinguished* were positive but not significant.

Hence, the results for the *Embeddedness* categories *Staff* and *Distinguished* failed to reject the null hypothesis. However, the results for the categories *Old School, Laggards* and *Rising Stars* found no support for Hypothesis 1. In fact, the results suggested that more embedded researchers were associated with a higher likelihood of commercial outcomes. Additional hypothesis testing was required to determine the predicted probability of commercialisation for each category of *Embeddedness* and establish the precise directionality of the effect. The results of this additional hypothesis testing can be found in Section 7.4.

6.5.4: Test of Hypothesis 2 - Firm Contribution

Hypothesis 2 was as follows:

Hypothesis 2: UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes.

The hypothesis was tested using two variables that measure the firmôs contribution relative to OCEôs contribution to the UIRCs under observation in this study: *Firm Cash Ratio* and *Firm In-kind Ratio.* The estimated test results for Hypothesis 2 are reported in Table 6.11.

Table 6.11: BNL and MNL Regression Results for Firm Characteristics

Firm Characteristics	**BNL Depvar = Commercialisation**				**MNL Depvar = Outcome by Type**			
			Fixed-Effects		**License**		**Startup**	
Hypothesis 2: Firm Contribution								
Firm Cash Ratio	-0.099	-(0.46)	-0.099	-(0.45)	-0.038	-(0.22)	-0.947	-(1.53)
Firm In-kind Ratio	0.335 ***	(2.52)	0.368 ***	(2.64)	0.495 ***	(3.35)	-0.084	-(0.31)
Control Variables:								
Firm Size [Small]								
Micro	0.129	(0.33)	0.165	(0.42)	0.342	(0.65)	-0.199	-(0.38)
Medium	-0.299	-(0.73)	-0.288	-(0.69)	-0.017	-(0.03)	-0.501	-(0.85)
Large	0.382	(0.93)	0.382	(0.91)	0.047	(0.08)	0.765	(1.42)
Firm Interaction	0.111	(1.39)	0.130	(1.53)	0.055	(0.49)	0.102	(0.89)
Number of Firms	0.138	(1.21)	0.124	(1.10)	0.256 **	(2.10)	-0.340	-(1.01)

Z-Scores in (parentheses) **Reference categories in [brackets]**
Significant at the * 0.1 level; ** 0.05; * 0.01**

The estimated coefficient for *Firm Cash Ratio* was negative but not significant. This was consistent with the results from Ambos et al. (2008). However, that study did not distinguish between cash and in-kind contributions made to UIRCs by firms.

The estimated coefficient for *Firm In-kind Ratio* was positive and significant for *Commercialisation*, and for the outcome *License* specifically. The relationship between *Firm In-kind Ratio* and the outcome *Startup* was negative but not statistically significant.

Hence, the results for *Firm Cash Ratio* failed to reject the null hypothesis. The results for *Firm In-kind Ratio* supported Hypothesis 2. However, the magnitude of the impact that a firmœs in-kind contribution has on commercial outcomes remains unclear. Additional hypothesis testing was required to determine the marginal effect that different amounts of in-kind contribution would have on the predicted probability of commercialisation. The results of this additional hypothesis testing can be found in Section 7.5.

6.5.5: Test of Hypothesis 3 - Industry Sectors

Hypothesis 3 was as follows:

> **Hypothesis 3: UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.**

The hypothesis was tested using a categorical variable representing each of the four industry sectors represented by OCEœs centres/divisions. The estimated test results for Hypothesis 3 are reported in Table 6.12.

Table 6.12: BNL and MNL Regression Results for Project Characteristics

Project Characteristics	BNL Depvar = Commercialisation				MNL Depvar = Outcome by Type			
			Fixed-Effects		License		Startup	
Hypothesis 3: Industry Sector								
Research Field [EET]								
CIT	1.985 ***	(3.42)	2.573 ***	(3.67)	2.287 ***	(3.15)	1.849	(1.63)
MM	1.714 ***	(3.23)	2.371 ***	(3.54)	1.581 **	(2.38)	2.464 **	(2.32)
Photonics	2.799 ***	(3.60)	3.484 ***	(4.05)	3.634 ***	(3.76)	3.097 **	(2.31)
Control Variables:								
Research Stage [Mid-stage]								
Earliest	1.415 ***	(3.53)	1.428 ***	(3.45)	2.346 ***	(3.23)	1.123 **	(2.26)
Latest	0.566	(0.77)	0.589	(0.79)	2.069 **	(1.95)	-0.792	-(0.68)
Funding per Month ($1000s)	0.059	(1.62)	0.054	(1.47)	0.048	(1.02)	0.091 *	(1.86)
Distance	-0.001 *	-(1.79)	-0.001 *	-(1.65)	-0.002 *	-(1.78)	-0.001	-(0.60)

Z-Scores in (parentheses) **Reference categories in [brackets]**
Significant at the * 0.1 level; ** 0.05; * 0.01**

The sign and significance levels of the categorical variable *Research Field* are interpreted relative to the omitted reference category Earth and Environmental Technology (*EET)*. The estimated coefficients for each *Research Field* were significant and positive relative to *EET*. The categories Communications and Information Technology (*CIT)*, Materials and Manufacturing (*MM)* and *Photonics* were significantly and positively associated with *Commercialisation*, and with both the outcomes *License* and *Startup* specifically. The only exception was the relationship between *CIT* and the outcome *Startup*, the estimate for which was slightly below the threshold for significance at the 10 percent level.

Hence, the results for *Research Field* offer preliminary support for Hypothesis 3. However, the magnitude of the sectoral differences in commercial outcomes remains unclear. Additional hypothesis testing was required to determine the predicted probability of commercialisation for each industry sector, and to compare it to each sectorӳ research intensity. The results of this additional hypothesis testing can be found in Section 7.6.

6.5.6: Results for Control Variables

This section describes the results for the studyӳ control variables. A summary of the estimated results for university control variables are reported in Table 6.13. A summary of the estimated results for other control variables were presented above in Tables 6.10, 6.11 and 6.12.

Table 6.13: BNL and MNL Regression Results for University Characteristics

University Characteristics	BNL Depvar = Commercialisation		MNL Depvar = Outcome by Type	
		Fixed-Effects	License	Startup
Control Variables:				
Research per Faculty	0.004** (2.43)	omitted	0.003 (1.25)	0.005*** (2.50)
University Operations	0.000 -(1.46)	omitted	0.000 (0.01)	0.000** -(2.00)
Inventions per TTO Staff	0.042*** (2.58)	omitted	0.071*** (3.07)	0.022 (0.97)
IP Ownership				
[University]				
Creator	-0.205 -(0.53)	omitted	-0.841 -(1.62)	0.569 (1.00)

Z-Scores in (parentheses) Reference categories in [brackets]
Significant at the * 0.1 level; ** 0.05; * 0.01**

The measures of university characteristics were omitted from the university fixed-effects model because the values for these predictors were fixed for each university.

Researcher Interaction: The estimated coefficient for *Researcher Interaction* was positive but not statistically significant for *Commercialisation*, but was positive and significant for the outcome *Startup.* Similarly, the level of previous researcher interaction was not a significant predictor of commercial outcomes in Ambos et al. (2008). Unfortunately, their study did not distinguish between types of outcome, therefore a direct comparison on the outcome *Startup* was not possible.

Gender: The relationship between *Commercialisation* and *Female* was negative and significant relative to the reference category *Male*. The estimated coefficient was slightly lower but still significant at the 10 percent level when adjusted for the fixed-effects of universities.[34] The predictor *Gender* was omitted from the MNL regression because the number of *Startup* outcomes in this sample for the category *Female* was zero, leading to perfect prediction. This was consistent with the results from the broader literature on university technology transfer and commercialisation.

Firm Size: The estimated coefficients for *Micro* and *Large* were positive, while the estimated coefficient for the category *Medium* was negative relative to the reference category *Small*. However, none were statistically significant. Comparatively, both Cohen et al. (2002) and Santoro and Gopalakrishnan (2001) found a significant, positive effect of

[34] This represents the only instance where the Fixed-Effects model differs from the regular BNL model with regard to the statistical significance of the predictors.

firm size on 1) the use of public research and 2) involvement in technology transfer, respectively.

Firm Interaction: The estimated coefficients for *Firm Interaction* were positive but not significant, and therefore contributed no new insights to previous results (Min and Kim, 2014, Mora-Valentin et al., 2004).

Number of Firms: The estimated coefficient for *Number of Firms* was positive but not statistically significant for *Commercialisation*. However, its relationship to the outcome *License* was positive and significant. The relationship between *Number of Firms* and the outcome *Startup* was negative but not statistically significant. This result may offer new insights since no other study was found that explores how the number of firms in a UIRC is associated with its commercial outcomes.

Research Stage: The sign and significance levels of the categorical variable *Research Stage* are interpreted relative to the omitted reference category *Mid-stage*.

The estimated coefficient for the *Earliest* stage was positive and highly significant for *Commercialisation* relative to *Mid-stage*, and for both the outcomes *License* and *Startup* specifically. This result was consistent with Gulbrandsen and Smeby (2005), who found that commercialisation was positively associated with basic research relative to applied research. Interestingly, the estimated coefficient for the *Latest* stage was also positive and significant for the outcome *License,* suggesting an intriguing relationship between later-stage research and licenses in particular.

Funding Per Month: The estimated coefficient for *Funding per Month* was positive but just below the threshold for significance for *Commercialisation*. However, the relationship between *Funding per Month* and the outcome *Startup* was positive and significant. In comparison, Ambos et al. (2008) found no significant relationship between UIRC project size and duration, and commercial outcomes.

Distance: The estimated coefficient for *Distance* was significant and negative for *Commercialisation* and for the outcome *License* specifically. The relationship between *Distance* and the outcome *Startup* was negative but not statistically significant. These results are consistent with a number of studies that found that greater proximity is important to effective research collaborations and drives more commercial outcomes (D'Este et al., 2012, Agrawal and Cockburn, 2003, Santoro and Gopalakrishnan, 2001, Mansfield, 1995).

Research per Faculty: The estimated coefficient for *Research per Faculty* was significant and positive. *Research per Faculty* was strongly related to *Commercialisation*, and with the outcome *Startup* specifically. The relationship between *Research per Faculty* and the outcome *License* was positive but not statistically significant. These results were consistent with OŠShea (2005), who found that the level of federal funding to a university was positively associated with startup activity.

University Operations: Conversely, the estimated coefficient for the alterative measure of university size *University Operations* was negative but slightly below the threshold for significance at the 10 percent level for *Commercialisation*. However, the relationship between *University Operations* and the outcome *Startup* was negative and significant. This provided conflicting evidence on the effect of university size on commercialisation from UIRCs, and on the creation of startups in particular.

Inventions per TTO Staff: The estimated coefficient for *Inventions per TTO Staff* was significant and positive. *Inventions per TTO Staff* was strongly related to *Commercialisation*, and with the outcome *License* specifically. Insofar as *Inventions per TTO Staff* can be considered a measure of breadth, these results offer a comparative view to Ambos et al. (2008), who found no significant relationship between breadth of TTO activities and commercial outcomes from UIRCs. The relationship between *Inventions per TTO Staff* and the outcome *Startup* was positive but not significant. Therefore, this study offered no new insights on the assessment by González-Pernía et al. (2013) that TTO size is positively associated with startups.

IP Ownership: Relative to the reference category *University,* the estimated coefficients for *Creator* were negative and not significant for *Commercialisation*. The coefficients for the outcome *License* was also negative but just below the threshold for significance at the .10 level. Conversely, the relationship between *Creator* and the outcome *Startup* was positive but not significant. Insofar as a creator-owned IP ownership policy could be considered an incentive to researchers, these results were consistent with Azagra-Caro et al. (2006), who found that higher incentives had no effect on faculty support for the objectives of UIRCs.

As a result of the analysis described above, 10 of 18 independent variables were found to be statistically significant or near significant in the BNL model, while 12 of 18 independent variables were found to be statistically significant or near significant in the MNL model.[35]

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[35] In Section 4.7.3., Likelihood Ratio Tests are conducted to assess the predictive capacity of categorical variables included in the ñfinalò BNL and MNL models.

6.6: Step 3 - Achieving Parsimony

Version 3 of the BNL and MNL models were specified using the remaining statistically significant or near significant independent variables (10 and 12 variables, respectively):

Table 6.14: Independent Variables in BNL Model Version 3

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • Embeddedness *Control Variable:* • Gender	*Hypothesis 2:* • Firm In-kind Ratio	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding per Month* • Distance*	*Control Variables:* • Research per Faculty • Uni. Operations* • Inventions per TTO Staff

* Indicates variables that were just below statistical significance at the 0.1 level

Table 6.15: Independent Variables in MNL Model Version 3

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • Embeddedness *Control Variable:* • Researcher Interaction	*Hypothesis 2:* • Firm In-kind Ratio *Control Variable:* • Number of Firms	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding per Month • Distance	*Control Variables:* • Research per Faculty • Uni. Operations • Inventions per TTO Staff • IP Ownership*

* Indicates variables that were just below statistical significance at the 0.1 level

BNL and MNL regressions were performed on *Version 3* of the models. The parameter estimates were analysed using the Wald test, with particular attention to the independent variables that were near or just below the threshold for statistical significance in *Version 2* of the model, to determine which predictors should be kept or omitted from the parsimonious models.

6.6.1: Analysis of BNL Model Version 3

Based on the analysis from Step 2, *Version 3* of the BNL model included seven statistically significant predictors, and three predictors with estimated coefficients near or just below the threshold for significance at the 10 percent level (*University Operations, Funding per Month, Distance*).

Table 6.16 presents the results of the BNL regression on *Version 3* of the model.

Table 6.16: BNL Regression Results on Model Version 3

Logistic regression				**LR chi2(17)**		**= 107.14**
Number of obs	**= 682**			**Prob > chi2**		**= 0**
Log likelihood	**= -188.91962**			**Pseudo R2**		**= 0.2209**
Commercialisation	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
Hypothesis 1: Embeddedness						
Embeddedness [New School]						
Staff	-0.364	1.177	-0.31	0.757	-2.672	1.943
Rising Stars	0.660	0.469	1.41	0.159	-0.259	1.579
Old School	1.031	0.385	2.68	0.007	0.277	1.785
Laggards	0.826	0.564	1.46	0.143	-0.280	1.932
Distinguished	0.720	0.773	0.93	0.352	-0.795	2.235
Hypothesis 2: Firm Contribution						
Firm In-kind Ratio	0.297	0.128	2.32	0.020	0.046	0.547
Hypothesis 3: Industry Sector						
Research Field [EET]						
CIT	1.872	0.546	3.43	0.001	0.801	2.942

MM	1.678	0.519	3.23	0.001	0.661	2.696
Photonics	2.743	0.750	3.66	0.000	1.272	4.213
Control Variables:						
Gender [Male]						
Female	-1.545	0.765	-2.02	0.043	-3.044	-0.046
Research per Faculty	0.004	0.002	2.69	0.007	0.001	0.007
University Operations	0.000	0.000	-1.42	0.156	0.000	0.000
Inventions per TTO Staff	0.042	0.015	2.75	0.006	0.012	0.072
Research Stage [Mid-stage]						
Earliest	1.447	0.396	3.66	0.000	0.672	2.223
Latest	0.699	0.709	0.99	0.324	-0.690	2.089
Funding per Month	0.000	0.000	1.75	0.080	0.000	0.000
Distance	-0.001	0.001	-1.46	0.145	-0.002	0.000
_cons	-5.647	1.273	-4.43	0.000	-8.143	-3.151

Reference categories in [brackets]

University Operations: The estimated coefficient for *University Operations*, which was just below the threshold for significance at the 10 percent level (z = -1.46) in *Version 2* of the model, remained not statistically significant in *Version 3* (z = -1.42).

Funding per Month: The estimated coefficient for *Funding per Month*, which was just below the threshold for significance level (z = 1.62) in *Version 2* of the model, was positive and significant at the 10 percent level in *Version 3* (z = 1.75).

Distance: The estimated coefficient for *Distance*, which was significant at the 10 percent level (z = -1.79) in *Version 2* of the model, was not significant in *Version 3* (z = -1.46).

As a result, *Funding per Month* was maintained in the final model, while *Distance* and *University Operations* were eliminated.

6.6.2: Analysis of MNL Model Version 3

Based on the analysis from Step 2, *Version 3* of the MNL model included 11 statistically significant predictors, and one predictor with an estimated coefficient just below the threshold for significance at the 10 percent level (*IP Ownership*). Table 6.17 presents the results of the MNL regression on *Version 3* model.

Table 6.17: MNL Regression Results on Model Version 3

Outcome by Type [Base Outcome: Failure]	License						Startup					
	Coef.	SE	z	P>z	[Conf. Int.]		Coef.	SE	z	P>z	[Conf. Int.]	
Hypothesis 1: Embeddedness												
Embeddedness [New School]												
Rising Stars	0.781	0.673	1.16	0.246	-0.538	2.101	1.025	0.652	1.57	0.116	-0.252	2.302
Old School	1.479	0.520	2.84	0.004	0.459	2.498	1.135	0.548	2.07	0.038	0.061	2.210
Laggards	-0.075	0.946	-0.08	0.937	-1.930	1.780	1.588	0.705	2.25	0.024	0.207	2.970
Distinguished	1.422	1.016	1.40	0.162	-0.570	3.414	0.482	1.200	0.40	0.688	-1.870	2.834
Hypothesis 2: Firm Contribution												
Firm In-kind Ratio	0.470	0.143	3.28	0.001	0.189	0.750	-0.126	0.251	-0.50	0.615	-0.619	0.366
Hypothesis 3: Industry Sector												
Research Field [EET]												
C/IT	2.267	0.715	3.17	0.002	0.867	3.668	1.977	1.109	1.78	0.075	-0.197	4.152
MM	1.553	0.664	2.34	0.019	0.252	2.854	2.507	1.059	2.37	0.018	0.431	4.584
Photonics	3.578	0.961	3.72	0	1.695	5.462	3.172	1.337	2.37	0.018	0.551	5.793
Control Variables:												
Researcher Interaction	-0.146	0.216	-0.68	0.499	-0.569	0.277	0.276	0.129	2.15	0.032	0.024	0.528
Number of Firms	0.256	0.119	2.16	0.031	0.023	0.489	-0.290	0.304	-0.96	0.339	-0.885	0.305
Research per Faculty	0.003	0.002	1.26	0.208	-0.002	0.007	0.005	0.002	2.39	0.017	0.001	0.009
University Operations	0.000	0.000	0.06	0.949	0.000	0.000	0.000	0.000	-1.75	0.080	-0.001	0.000
Inventions per TTO Staff	0.069	0.022	3.10	0.002	0.025	0.113	0.029	0.022	1.30	0.193	-0.015	0.072
IP Ownership [University]												
Creator	-0.821	0.487	-1.69	0.092	-1.776	0.133	0.304	0.552	0.55	0.581	-0.777	1.385
Research Stage [Mid-stage]												
Earliest	2.305	0.714	3.23	0.001	0.905	3.705	1.187	0.489	2.43	0.015	0.229	2.144
Latest	1.930	1.035	1.87	0.062	-0.098	3.959	-0.345	1.131	-0.31	0.760	-2.563	1.872
Funding per Month	0.000	0.000	1.06	0.289	0.000	0.000	0.000	0.000	1.67	0.095	0.000	0.000
Distance	-0.002	0.001	-1.78	0.076	-0.003	0.000	-0.001	0.001	-0.61	0.543	-0.002	0.001
_cons	-8.836	1.937	-4.56	0	-12.63	-5.04	-5.614	2.028	-2.77	0.006	-9.590	-1.64

The estimated coefficient for *IP Ownership*, which was just below the threshold for significance level (z = -1.62) in *Version 2* of the model, was negative and significant at the 10 percent level in *Version 3* (z = -1.69). As a result, *IP Ownership* was maintained in the final MNL model.

6.7: Step 4: Goodness-of-Fit

The final models were subjected to a number of overall goodness-of-fit tests to demonstrate that they are the most parsimonious models possible.

6.7.1: Analysis of the Final BNL Model

The final BNL model presented in Table 6.18 included eight significant predictors:

Table 6.18: Final BNL Model Results

Logistic Regression			LR chi2(15)		=	101.35
Obs.	= 682		Prob > chi2		=	0
Log likelihood	= -191.81372		Pseudo R2		=	0.209
	Coef.	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
Hypothesis 1: Embeddedness						
Embeddedness [New School]						
Staff	-0.419	1.153	-0.36	0.716	-2.680	1.842
Rising Stars	0.757	0.464	1.63	0.103	-0.153	1.666
Old School	1.114	0.379	2.94	0.003	0.371	1.856
Laggards	0.978	0.557	1.76	0.079	-0.113	2.069
Distinguished	0.759	0.761	1.00	0.318	-0.732	2.251
Hypothesis 2: Firm Contribution						
Firm In-kind Ratio	0.309	0.128	2.42	0.016	0.058	0.560
Hypothesis 3: Industry Sectors						
Research Field [EET]						
C/IT	1.985	0.538	3.69	0.000	0.931	3.040
MM	1.750	0.516	3.39	0.001	0.739	2.761
Photonics	2.845	0.745	3.82	0.000	1.385	4.305
Control Variables:						
Gender [Male]						
Female	-1.484	0.760	-1.95	0.051	-2.974	0.006
Research per Faculty	0.004	0.001	2.72	0.007	0.001	0.007
Inventions per TTO Staff	0.044	0.015	2.93	0.003	0.015	0.074
Research Stage [Mid-stage]						
Earliest	1.360	0.390	3.49	0.000	0.596	2.124
Latest	0.684	0.706	0.97	0.333	-0.700	2.068
Funding per Month	0.000	0.000	1.92	0.055	0.000	0.000
_cons	-7.294	0.829	-8.8	0.000	-8.919	-5.669

The ñfinalò BNL model was further analysed using a number goodness-of-fit tests, which compared it to previous versions of the model. Table 6.19 presents selected comparative results. The complete goodness-of-fit test results can be found in Appendix E.

Table 6.19: Goodness of Fit Tests for Final BNL Model

	Final Model	Version 3 Model	Version 2 Model
N:	682	682	682
Log-Lik Full Model:	-191.814	-188.92	-185.676
McFadden's R2:	0.209	0.221	0.234
McFadden's Adj R2:	0.126	0.13	0.102
AIC*n:	423.627	421.839	435.352
BIC':	-3.473	3.789	49.502

The difference in the log likelihood between the final model and *Version 2* (-6.14) suggested that, with its 10 additional independent variables, *Version 2* predicted only negligibly better than the final model. The difference in McFaddenôs R^2 (.025) also suggested that the accuracy of *Version 2* was only negligibly better, or worse in the case of McFaddenôs adjusted R^2 (.024), than the final model. In addition, the difference in the information criterion measures including Akaike's Information Criterion (AIC*n = -11.73) and the Bayesian Information Criterion (BIC' = -52.98) provided very strong support for final BNL model.

6.7.2: Analysis of the Final MNL Model

The final MNL model included 12 statistically significant predictors, including eight that were significant predictors of a *License*, seven that were significant predictors of a *Startup*, and three that were significant predictors of both. Since the independent variable *IP Ownership* was kept in the model after the analysis in Step 3, there is no difference between *Version 3* of the model and the final MNL model, which is presented in Table 6.20:

Table 6.20: Final MNL Model Results

Outcome by Type	License						Startup					
	Coef.	SE	z	P>z	[Conf. Int.]		Coef.	SE	z	P>z	[Conf. Int.]	
Hypothesis 1: Embeddedness												
Embeddedness [New School]												
Rising Stars	0.781	0.673	1.16	0.246	-0.538	2.101	1.025	0.652	1.57	0.116	-0.252	2.302
Old School	1.479	0.520	2.84	0.004	0.459	2.498	1.135	0.548	2.07	0.038	0.061	2.210
Laggards	-0.075	0.946	-0.08	0.937	-1.930	1.780	1.588	0.705	2.25	0.024	0.207	2.970
Distinguished	1.422	1.016	1.40	0.162	-0.570	3.414	0.482	1.200	0.40	0.688	-1.870	2.834
Hypothesis 2: Firm Contribution												
Firm In-kind Ratio	0.470	0.143	3.28	0.001	0.189	0.750	-0.126	0.251	-0.50	0.615	-0.619	0.366
Hypothesis 3: Industry Sector												
Research Field [EET]												
C/IT	2.267	0.715	3.17	0.002	0.867	3.668	1.977	1.109	1.78	0.075	-0.197	4.152
MM	1.553	0.664	2.34	0.019	0.252	2.854	2.507	1.059	2.37	0.018	0.431	4.584
Photonics	3.578	0.961	3.72	0	1.695	5.462	3.172	1.337	2.37	0.018	0.551	5.793
Control Variables:												
Researcher Interaction	-0.146	0.216	-0.68	0.499	-0.569	0.277	0.276	0.129	2.15	0.032	0.024	0.528
Number of Firms	0.256	0.119	2.16	0.031	0.023	0.489	-0.290	0.304	-0.96	0.339	-0.885	0.305
Research per Faculty	0.003	0.002	1.26	0.208	-0.002	0.007	0.005	0.002	2.39	0.017	0.001	0.009
University Operations	0.000	0.000	0.06	0.949	0.000	0.000	0.000	0.000	-1.75	0.080	-0.001	0.000
Inventions per TTO Staff	0.069	0.022	3.10	0.002	0.025	0.113	0.029	0.022	1.30	0.193	-0.015	0.072
IP Ownership [University]												
Creator	-0.821	0.487	-1.69	0.092	-1.776	0.133	0.304	0.552	0.55	0.581	-0.777	1.385
Research Stage [Mid-stage]												
Earliest	2.305	0.714	3.23	0.001	0.905	3.705	1.187	0.489	2.43	0.015	0.229	2.144
Latest	1.930	1.035	1.87	0.062	-0.098	3.959	-0.345	1.131	-0.31	0.760	-2.563	1.872
Funding per Month	0.000	0.000	1.06	0.289	0.000	0.000	0.000	0.000	1.67	0.095	0.000	0.000
Distance	-0.002	0.001	-1.78	0.076	-0.003	0.000	-0.001	0.001	-0.61	0.543	-0.002	0.001
_cons	-8.836	1.937	-4.56	0	-12.63	-5.04	-5.614	2.028	-2.77	0.006	-9.590	-1.64

Failure is the base outcome

The final MNL model was further analysed using the same goodness-of-fit tests, which compared it to those of the *Version 2* of the model. Table 6.21 presents the comparative results.

Table 6.21: Goodness-of-Fit Tests for Final MNL Model

	Final Model	Version 2 Model	Difference
N:	663	663	0
Log-Lik Full Model:	-225.065	-220.863	-4.202
LR:	132.848(36)	141.252(46)	-8.404(-10)
Prob > LR:	0	0	0
McFadden's R2:	0.228	0.242	-0.014
McFadden's Adj R2:	-0.009	-0.056	0.047
AIC*n:	588.131	615.727	-27.596
BIC':	101.036	157.6	-56.564

The difference in the log likelihood (-4.20), likelihood ratio (-8.40) and p-value (0.000) suggested that *Version 2* of the model, with its six additional independent variables, predicted only negligibly better than the final model. The difference in McFaddenôs R^2 (.014) also suggested that the accuracy of *Version 2* was only negligibly better, or worse in the case of McFaddenôs adjusted chi-square (0.047), than the final model. In addition, the difference in the information criterion measures including Akaike's Information Criterion (AIC*n = -27.60) and Bayesian Information Criterion (BIC' = -56.56) provided strong support for the final MNL model.

6.7.3: Likelihood Ratio Tests

Since the parameter estimates in the final BNL and MNL models for the categorical variables *Embeddedness*, *Research Stage*, and *Research Field* were interpreted relative to their omitted reference categories, additional tests were performed to assess the joint statistical significance of each of these groups of variables. Likelihood ratio tests were used to compare the fit of the final BNL and MNL models with and without each categorical variable. The results of the likelihood ratio tests are presented in Table 6.22.

Table 6.22: Likelihood Ratio Tests for Categorical Variables

Categorical	BNL Model			MNL Model		
Variable:	**LR chi2**	***df***	**Prob > chi2**	**LR chi2**	***df***	**Prob > chi2**
Embeddedness	9.15	5	0.1034	17.75	8	0.0232
Research Stage	15.37	2	0.0005	21.03	4	0.0003
Research Field	21.55	3	0.0001	28.69	6	0.0001
Firm Size	2.41	3	0.4912	4.72	6	0.5798

The likelihood ratio test statistics and their associated *p*-values indicated that adding *Embeddedness*, *Research Stage* and *Research Field* individually resulted in a statistically significant improvement in the fit of both models. The test statistics were significant at the 1% level, with the exception of *Embeddedness*, which was significant at the 5% level in the MNL model and near significant at the 10% level in the BNL model. The likelihood ratio test statistics and associated p-values for *Firm Size* confirm that the variable does not improve the fit of the BNL or MNL models in a statistically significant way (p = .4912 and p = .5798, respectively).

6.8: Chapter Summary

The statistical analysis involved the application of two forms of Discrete Choice Modeling (DCM), Binomial Logit (BNL) and Multinomial Logit (MNL), composed of binary and polychotomous categorical dependent variables, respectively. *Version 1* of the model began with five independent variables used to test the three hypotheses, and 19 control variables. Using correlation matrices, bivariate regressions and the Variance Inflation Factor to address multicollinearity, *Version 2* of the model was reduced to sixteen independent variables: three related to the hypotheses, and 13 control variables. Multivariate regressions were then used to identify respectively 10 and 12 independent variables in *Version 3* of the BNL and MNL models that were statistically significant or near significant. Additional Goodness-of-Fit and Likelihood Ratio tests were conducted to determine the most parsimonious model possible.

The hypothesis test results were as follows:

> **Hypothesis 1:** The data did not support the hypothesis that UIRCs involving researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.
>
> **Hypothesis 2:** The data for *Firm Cash Ratio* did not support the hypothesis, while the data for *Firm In-kind Ratio* did support the hypothesis, that UIRCs with higher contributions by firms will be associated with a higher likelihood of commercial outcomes.
>
> **Hypothesis 3:** The data for Research Field supported the hypothesis that UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.

Five additional control variables were associated with *Commercialisation* in the BNL model.

At the 1 percent level:

- Research per Faculty (+)
- Research Stage (+)
- Inventions per TTO Staff (+)

At the 10 percent level:

- Funding per Month (+)
- Gender (for which *Female* was negatively associated)

In the MNL model, five additional control variables were associated only with a *License*.

At the one percent level:

- Research Stage (+)
- Inventions per TTO Staff (+)

At the five percent level:

- Number of Firms (+)

At the 10 percent level:

- IP Ownership (for which *Creator* ownership was negatively associated)
- Distance (-)

In addition, five additional control variables were associated only with a *Startup.*

At the five percent level:

- Research per Faculty (+)
- Research Stage (+)
- Researcher Interaction (+)

At the 10 percent level:

- University Operations (-)
- Funding per Month (+)

CHAPTER VII: RESULTS

With the models now specified, this chapter discusses the results by outcome for each significant independent variable.

7.1: Introduction

Section 7.2 outlines the options considered for interpreting the results and provides a rationale for the selected approach.

Section 7.3 summarises the results for commercialisation, and for both licenses and startups specifically.

Sections 7.4, 7.5 and 7.6 discuss the magnitude of the hypothesis test results for *Embeddedness*, *Firm Contribution* and *Industry Sector*, respectively, and provide additional analysis that improves the interpretation of the results.

Section 7.7 discusses the magnitude of the results for the control variables used in the model.

7.2: Magnitude of the Results

In the previous chapter, the z-statistic and associated p-values from the Binomial Logit (BNL) and Multinomial Logit (MNL) regressions were interpreted to test the three hypotheses and to specify the most parsimonious model. In this chapter, the BNL and MNL parameter estimates were used to determine the predicted probabilities of commercial outcomes of the three independent variables used to test the hypotheses. The predicted probability of each of the control variables is also discussed.

BNL and MNL regression coefficients express the change in the log odds of the outcome for a given change in the independent variable, holding all other independent variables constant. Log odds are not intuitive to understand or interpret. Following Long and Freese (2014), a number of standardisation techniques were considered in order to make the results more informative and pertinent to the research questions.

Odds Ratios: The odds ratio is the comparison of the relative odds for two groups. It can be obtained by exponentiating the regression coefficients. For continuous independent variables, the odds ratio shows how many ñtimesò more (or less) likely the odds are as a result of a one unit change in the variable. For categorical variables, the odds ratio shows how many ñtimesò more likely one category is relative to the reference category.

Adjusted Predictions: The parameter estimates can be used to estimate the predicted probability of a given event. For categorical independent variables, the probability of *Commercialisation* associated with each category can be predicted. For continuous independent variables, the probability of *Commercialisation* can be predicted for any given value for the variable. Common methods for estimating predicted probabilities include Average Adjusted Predictions (AAP) and Adjusted Predictions at the Means (APM), which differ in the way they control for the other variables in the model (Williams, 2012). AAP uses the actual observed values for the other independent variables, while APM uses the mean values for the other independent variables. Many researches prefer AAP because it makes better use of all the data available and does not use a set of values that no real person could actually have (e.g. no person can be 11.2% female) (Williams, 2012).

Marginal Effects: Marginal effects represent the change in outcome for a given change in an independent variable, holding all other variables in the model constant. They can be interpreted in the same way as estimated coefficients in a linear regression. For categorical variables, marginal effects can be used to assess the predicted probability of a given category relative to the reference category. For continuous variables, they can be used to assess the change in the predicted probability of *Commercialisation* as a result of a unit change in the variable. Marginal effects can also be estimated using Average Marginal Effects (AME) and Marginal Effects at the Means (MEM).

Adjusted predictions were selected over odds ratios for interpreting the studyộs results because they are easier to understand and are directly relevant to the research questions and hypothesis testing. For each continuous variable, marginal effects were also calculated for the range of values found in the sample.

7.3: Summary of Results by Commercial Outcome

This section provides an overview of the marginal effects by commercial outcome, including for commercialisation overall, and for licenses or startups specifically. A detailed discussion of the results for each hypothesis, and for each of the control variables, is provided in Sections 7.4 through 7.7.

7.3.1: Summary of Results for Commercialisation

The following eight independent variables were associated with *Commercialisation* in the final BNL model.

Table 7.1: Characteristics Associated with Commercialisation

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • Embeddedness *Control Variable:* • Gender	*Hypothesis 2:* • Firm In-kind Ratio	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding per Month	*Control Variables:* • Inventions per TTO Staff • Research per Faculty

Table 7.2 shows the marginal effects for these eight independent variables. As discussed in the descriptive statistics in Section 5.7, the average probability of *Commercialisation* (i.e. license or a startup) in the sample is 11.4 percent.

Table 7.2: Marginal Effects for Commercialisation

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Hypothesis 1:						
Embeddedness [New School]						
Staff	-0.019	0.046	-0.41	0.678	-0.110	0.071
Rising Stars	0.053	0.034	1.56	0.119	-0.014	0.119
Old School	0.088	0.027	3.23	0.001	0.034	0.141
Laggards	0.074	0.048	1.52	0.128	-0.021	0.168
Distinguished	0.053	0.063	0.84	0.399	-0.070	0.177
Hypothesis 2:						
Firm In-kind Ratio	0.026	0.011	2.43	0.015	0.005	0.047
Hypothesis 3:						
Research Field [EET]						
CIT	0.126	0.032	3.93	0.000	0.063	0.188
MM	0.101	0.023	4.35	0.000	0.056	0.147
Photonics	0.240	0.088	2.72	0.007	0.067	0.414
Control Variables:						
Gender [Male]						
Female	-0.087	0.027	-3.17	0.002	-0.140	-0.033
Research per Faculty ($100,000s)	0.033	0.000	2.75	0.006	0.000	0.001
Inventions per TTO Staff	0.004	0.001	2.96	0.003	0.001	0.006
Funding per Month ($10,000s)	0.055	0.000	1.94	0.052	0.000	0.000
Research Stage [Mid-stage]						
Earliest	0.102	0.025	4.05	0.000	0.053	0.152
Latest	0.040	0.049	0.82	0.410	-0.055	0.135

Reference categories in [brackets]

7.3.2: Summary of Results for the Outcome 'License'

The following eight independent variables were associated with a *License* in the final MNL model. As discussed in the descriptive statistics in Section 5.7, the average probability of a *License* in the sample is 5.8 percent.

Table 7.3: Characteristics Associated with a License

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • Embeddedness	*Hypothesis 2:* • Firm In-kind Ratio *Control Variable:* • Number of Firms	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Distance	*Control Variables:* • Inventions per TTO staff • IP Ownership

The marginal effects for the predictors of the dependent variable *License* are presented in Table 7.4.

Table 7.4: Marginal Effects for a License

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Hypothesis 1:						
Embeddedness [New School]						
Rising Stars	0.024	0.024	0.98	0.328	-0.024	0.071
Old School	0.061	0.020	3.01	0.003	0.021	0.101
Laggards	-0.006	0.021	-0.26	0.791	-0.047	0.036
Distinguished	0.062	0.061	1.00	0.317	-0.059	0.182
Hypothesis 2:						
Firm In-kind Ratio	0.023	0.007	3.30	0.001	0.009	0.036
Hypothesis 3:						
Research Field [EET]						
CIT	0.088	0.029	3.03	0.002	0.031	0.145
MM	0.041	0.017	2.44	0.015	0.008	0.074
Photonics	0.201	0.084	2.39	0.017	0.036	0.367
Control Variables:						
Number of Firms	0.014	0.006	2.42	0.015	0.003	0.024
Inventions per TTO Staff	0.003	0.001	2.90	0.004	0.001	0.005

IP Ownership [University]						
Creator	-0.048	0.032	-1.50	0.133	-0.111	0.015
Research Stage [Mid-stage]						
Earliest	0.071	0.016	4.32	0.000	0.039	0.103
Latest	0.056	0.043	1.29	0.198	-0.029	0.140
Distance (100kms)	0.007	0.000	-1.70	0.089	0.000	0.000

Reference categories in [brackets]

7.3.3: Summary of Results for the Outcome 'Startup'

The following seven independent variables were associated with a *Startup* in the final MNL model.

Table 7.5: Characteristics Associated with a Startup

Researcher Characteristics	Firm Characteristics	Project Characteristics	University Characteristics
Hypothesis 1: • Embeddedness *Control Variable:* • Interaction	• Not significant (n.s.)	*Hypothesis 3:* • Research Field *Control Variables:* • Research Stage • Funding per Month	*Control Variables:* • Research per Faculty • University Operations

The marginal effects for the predictors of the dependent variable *Startup* are presented in Table 7.6.

Table 7.6: Marginal Effects for a Startup

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Hypothesis 1:						
Embeddedness [New School]						
Rising Stars	0.037	0.026	1.42	0.156	-0.014	0.089
Old School	0.039	0.019	2.06	0.040	0.002	0.076
Laggards	0.079	0.043	1.84	0.066	-0.005	0.164
Distinguished	0.010	0.039	0.26	0.792	-0.067	0.087
Hypothesis 2:						
Firm Cash Ratio	n.s.					
Firm In-kind Ratio	n.s.					
Hypothesis 3:						
Research Field [EET]						
CIT	0.039	0.019	2.08	0.038	0.002	0.075
MM	0.072	0.019	3.80	0.000	0.035	0.108
Photonics	0.093	0.066	1.41	0.158	-0.036	0.222
Control Variables:						
Researcher Interaction	0.014	0.006	2.25	0.025	0.002	0.027
Research per Faculty ($100,000s)	0.023	0.000	2.21	0.027	0.000	0.000
University Operations ($1,000s)	0.000	0.000	-1.74	0.083	0.000	0.000
Research Stage [Mid-stage]						
Earliest	0.048	0.021	2.33	0.020	0.008	0.089
Latest	-0.011	0.024	-0.45	0.653	-0.058	0.036
Funding per Month	0.000	0.000	1.57	0.115	0.000	0.000

Reference categories in [brackets]

As discussed in the descriptive statistics in Section 5.7, the average probability of a *Startup* in the sample is 5.5 percent.

7.4: Results for Hypothesis 1 - Embeddedness

Hypothesis 1 was as follows:

> **Hypothesis 1: UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.**

The test of Hypothesis 1 in Section 6.5.3 found that the *Embeddedness* categories *Staff* and *Distinguished* failed to reject the null hypothesis. However, the results for *Old School*, *Laggards* and *Rising Stars* found no support for Hypothesis 1. In fact, the results suggested the opposite. Additional hypothesis testing was conducted to determine the predicted probability of commercialisation for each category of *Embeddedness*. The predicted probabilities were then used to determine the precise directionality of the relationship; that is, whether the categories that represented greater *Embeddedness* had a higher predicted probability of commercialisation than the categories that represented lower *Embeddedness*.

Table 7.7 presents the predicted probabilities of *Commercialisation* for each category of *Embeddedness*:[36]

[36] As discussed in Section 6.5.2, the category *Staff* was omitted from the final MNL model to avoid perfect prediction.

Table 7.7: Predicted Probabilities for Embeddedness

	Commercial-isation	License	Startup
Embeddedness			
Staff	0.043*	N/A	N/A
New School	0.062	0.030	0.028
Rising Stars	0.115	0.053*	0.065
Laggards	0.136	0.024*	0.107
Old School	0.150	0.091	0.067
Distinguished	0.115*	0.091*	0.038*

* categories were not statistically significant

The categories are presented in Table 7.7 in ascending order of *Embeddedness*. The predicted probabilities for *Commercialisation* provided evidence that the likelihood of commercial outcomes increased with greater levels of *Embeddedness.* The probability of achieving *Commercialisation* was 15 percent among the *Old School* and 13.6 percent among *Laggards*. The probability was 8.8 percentage points greater for the *Old School* and 7.4 percentage points greater for *Laggards* compared to the reference category *New School*.

The results for the outcome *License* were consistent with those for *Commercialisation* in finding no support for Hypothesis 1. The probability of a *License* was 9.1 percent among the *Old School* and three percent among *New School*, a difference of 6.1 percentage points. The estimated coefficients for the other categories of *Embeddedness* were not a statistically significant predictor of a *License* in the final MNL model.

However, the results were more nuanced for the predicted probabilities of the outcome *Startup*. *Laggards* had the highest predicted probability of a *Startup* at 10.7 percent, followed by the *Old School* at 6.7 percent and the *Rising Stars* at 6.5, then finally the *New School* at 2.8 percent. *Distinguished* was not a statistically significant predictor for *Startup* in the final MNL model.

Interestingly, these results contrasted those of Ambos et al. (2008), who found a significant but negative relationship between both measures of *Embeddedness* and commercialisation from UIRCs. This was an important result from this study. A number of factors may have contributed to the differences in these results. In addition, there were a number of reasons why the *Laggards* may have outperformed the *Old School* with regard to startup activity. Both issues are further discussed in the interpretation of the results in Section 8.2.1.

7.5: **Results for Hypothesis 2 - Firm Contribution**

Hypothesis 2 was as follows:

> **Hypothesis 2: UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes.**

The test of Hypothesis 2 in Section 6.5.4 found that *Firm Cash Ratio* failed to reject the null hypothesis. However, the test results for Firm *In-kind Ratio* supported Hypothesis 2. Additional hypothesis testing was conducted to determine the marginal effect that different amounts of in-kind contribution would have on the predicted probability of commercialisation.

When a firm increased the ratio of its in-kind contribution by a factor of one compared to OCEôs contribution, the average rate of increase in the probability of *Commercialisation* was 2.6 percentage points. This rate of increase in the probability was constant for all possible values, which was not meaningful given that the range of values for *Firm In-kind Ratio* found within the sample was between 0 and 11.4. Therefore, Figure 7.1 shows the probability of *Commercialisation* over this more useful range of values.

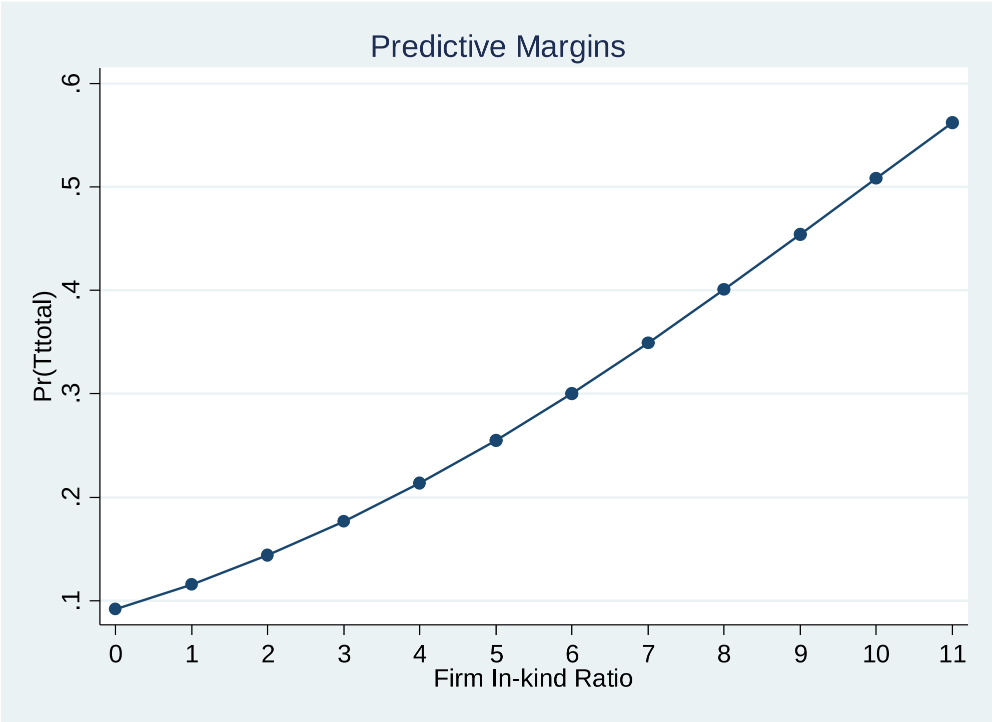

Fig. 7.1: Predicted Margins for Firm In-kind Ratio

Figure 7.1 illustrated that the effect *on Commercialisation* of different levels of in-kind contribution was not linear. The rate of increase was greater than average over the range of values for *Firm In-kind Ratio* found within the sample, with the exception of between zero and one, where the rate of increase was 2.4 percentage points.

These results provided additional evidence in support of Hypothesis 2 and demonstrated that higher ratios of firm in-kind increased the growth rate in the predicted probability of commercialisation. For greater clarity, Table 7.8 shows the predicted probabilities at representative values within the range of the sample.

Table 7.8: Predicted Probabilities of Commercialisation for Firm In-kind Ratio

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Firm In-kind Ratio						
0	0.092	0.013	7.04	0.000	0.066	0.117
1	0.116	0.011	10.34	0.000	0.094	0.138
2	0.144	0.018	8.07	0.000	0.109	0.179
3	0.177	0.032	5.55	0.000	0.114	0.239
4	0.214	0.050	4.24	0.000	0.115	0.313
5	0.255	0.072	3.52	0.000	0.113	0.397
6	0.301	0.097	3.09	0.002	0.110	0.491
7	0.349	0.124	2.83	0.005	0.107	0.591
8	0.401	0.150	2.66	0.008	0.106	0.696
9	0.454	0.176	2.58	0.010	0.109	0.800
10	0.508	0.200	2.55	0.011	0.117	0.900
11	0.563	0.219	2.57	0.010	0.133	0.992

The probability of *Commercialisation* increased from 9.2 percent to 17.7 percent for a UIRC in which the firm made an in-kind contribution of three dollars for every dollar contributed by OCE, compared to a UIRC in which the firm made no in-kind contribution.

The results for the outcome *License* were consistent with those for *Commercialisation* in finding support for Hypothesis 2. The probability of a *License* increased by an average of 2.3 percentage points when a firm increased the ratio of its in-kind contribution by a factor of one compared to OCEʼs contribution. Table 7.9 shows the probability of a *License* over the range of values for *Firm In-kind Ratio* found within the sample for this study (0-11.4).

Table 7.9: Predicted Probabilities of a License for Firm In-kind Ratio

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Firm In-kind Ratio						
0	0.040	0.008	5.03	0.000	0.024	0.056
1	0.059	0.009	6.91	0.000	0.042	0.076
2	0.086	0.014	6.18	0.000	0.059	0.113
3	0.121	0.026	4.71	0.000	0.070	0.171
4	0.164	0.043	3.83	0.000	0.080	0.248
5	0.216	0.064	3.36	0.001	0.090	0.341
6	0.274	0.088	3.12	0.002	0.102	0.447
7	0.339	0.112	3.02	0.003	0.119	0.559
8	0.406	0.135	3.00	0.003	0.141	0.671
9	0.475	0.155	3.06	0.002	0.171	0.780
10	0.544	0.171	3.18	0.001	0.209	0.879
11	0.610	0.181	3.37	0.001	0.255	0.966

As with *Commercialisation*, the rate of increase was higher than average over the sample range, with the exception of between zero and one, which had a rate of increase of 1.9 percentage points. The probability of a license was 8.1 percentage points greater for a UIRC in which the firm made an in-kind contribution of three dollars for every dollar contributed by OCE, compared to a UIRC in which the firm made no in-kind contribution.

The relative significance of in-kind contributions to UIRCs by firms over cash contributions was an important result of this study. These additional insights on different types of firm contributions help to elucidate the results from previous studies that examined the role of firms in UIRCs. The implications of these results on the additionality created by government subsidies are also further discussed in the interpretation of the results in Section 8.2.2.

7.6: Results for Hypothesis 3 - Industry Sectors

Hypothesis 3 was as follows:

> **Hypothesis 3: UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.**

The hypothesis test in Section 6.5.5 found a statistically significant relationship between *Research Field* and commercial outcomes from UIRCs, which provided preliminary support for Hypothesis 3. Additional hypothesis testing was conducted to determine the predicted probability of commercialisation for each industry sector, and to compare it to each sectorŝ research intensity.

Table 7.10 shows the predicted probabilities of *Commercialisation* in each *Research Field*.

Table 7.10: Predicted Probabilities of Commercialisation for Research Field

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Field						
CIT	0.155	0.029	5.29	0.000	0.097	0.212
MM	0.130	0.019	6.84	0.000	0.093	0.167
EET	0.029	0.013	2.28	0.023	0.004	0.054
Photonics	0.269	0.087	3.08	0.002	0.098	0.441

The probability of *Commercialisation* was highest in the field of Photonics by a significant margin (26.9%), followed by 15.5 percent and 13 percent in the fields of Communications and Information Technology (CIT) and Materials and Manufacturing (MM), respectively. The probability of *Commercialisation* is 24 percentage points greater in the field of Photonics compared to the reference field of Earth and Environmental Technology (EET).

Table 7.11 shows the predicted probabilities of a *License* in each *Research Field*.

Table 7.11: Predicted Probabilities of a License for Research Field

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Field						
CIT	0.105	0.027	3.87	0.000	0.052	0.158
MM	0.058	0.014	4.20	0.000	0.031	0.086
EET	0.017	0.009	1.97	0.048	0.000	0.034
Photonics	0.219	0.083	2.62	0.009	0.055	0.382

The results for the outcome *License* were consistent with those for *Commercialisation*. The highest probability of a *License* was in the field of Photonics at 21.9 percent. The field with the next highest probability was CIT at 10.5 percent. A UIRC in the field of Photonics had a 20.2 percentage point greater probability of a *License* compared to the field of EET.

Table 7.12 shows the predicted probabilities of achieving a *Startup* in each *Research Field*.

Table 7.12: Predicted Probabilities of a Startup for Research Field

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Field						
CIT	0.048	0.016	2.95	0.003	0.016	0.079
MM	0.080	0.017	4.83	0.000	0.048	0.113
EET	0.009	0.009	1.00	0.317	-0.008	0.026
Photonics	0.102	0.065	1.56	0.118	-0.026	0.229

The results for the outcome *Startup* were slightly more nuanced. Photonics remained the field with the highest predicted probability of a *Startup* at 10.2 percent. However, the next highest in the case of a *Startup* was MM at eight percent, followed by CIT at 4.8 percent. EET continued to lag behind other fields.

In order to complete the hypothesis testing, the predicted probabilities of commercialisation in each industry sector were compared to the research intensity in those industries, as discussed in Section 2.3. Making a direct comparison between the industry sectors represented by OCEôs four centres and the publicly available information on sector-specific research intensity was a challenge in some cases. The sectors related to MM were relatively straightforward, and included Fabricated Metal Products, Motor Vehicles, Plastic and Chemicals, and Mechanical and Electrical Machinery. The sectors related to EET were also evident and included Basic Metals, Wood and Paper, and Aerospace.

However, it was not possible to disambiguate the two remaining OCE centres, CIT and Photonics. CIT clearly belonged to the industry sectors of Office and Computer Equipment and Radio and Telecommunications Equipment. On the other hand, Photonics is the technical study of light but its practical application in the province of Ontario was related almost exclusively to technologies used in fiber optic telecommunications equipment. As described in Section 2.3, the presence of Nortel as Canadaøs largest technology company, and one of the worldøs dominant telecommunications equipment companies, helped to create an important technology cluster in this field in Ontario. Given the strategic importance of photonics in Ontario, the provincial government created a photonics centre within OCE. It was a relatively small and highly specialised centre compared to the other three. As described in the descriptive statistics in Section 5.8, only 25 of the 682 observations in the sample for this study were in the *Research Field* of Photonics.

Notwithstanding the strategic importance of photonics to Ontario, this field of research was, in reality, a sub-sector of Communications and Information Technology. In order to more directly compare sectoral differences for the purposes of testing hypothesis 3, the 25 observations related to the *Research Field* of Photonics were recoded as CIT. The category Photonics was eliminated from *Research Field*, leaving three categories (CIT, MM and EET), and the Final BNL model was re-estimated using this new categorisation.

The BNL regression results using the new categorisation of *Research Field* are presented in Appendix F. The fields of CIT and MM remained positive and significant relative to the omitted reference category EET. The estimation results for all other independent variables were not significantly different from the previous model.

Table 7.13 shows the updated predicted probabilities of *Commercialisation* for the new categorisation of *Research Field*, and compares them to the research intensity of each industry sector.

Table 7.13: Prob. of Commercialisation and Research Intensity by Industry Sector

Research Field	Predicted Prob.	Industry Sector	Research Intensity	Share of GDP
CIT	17.10%	Office and Computer Equip	53.63%	0.10%
		Radio & Telecom Equip.	27.87%	1.10%
MM	12.80%	Fab. Metal Products	1.03%	1.23%
		Motor Vehicles	0.75%	2.86%
		Plastic and Chemicals	1.63%	2.21%
		Mech. & Elect. Machinery	2.09%	1.26%
EET	2.90%	Basic Metals	1.28%	1.15%
		Other Mining Products	0.29%	0.13%
		Wood and Paper	0.39%	4.13%
		Other transport (incl. aerospace)	14.48%	0.88%

The results shown in Table 7.13 provided additional evidence in support of Hypothesis 3 and demonstrated that UIRCs in industry sectors with higher research intensity was associated with a higher likelihood of commercial outcomes. The highest probability of *Commercialisation* was in the field of CIT, whose related industry sectors also had drastically higher research intensity than other Canadian industries. The probability of *Commercialisation* in the field of MM was 5.3 percentage points lower. However, the research intensity of MM-related industry sectors is considerable lower than those related to CIT. Interestingly, the probability of *Commercialisation* in the field of EET was considerably lower (2.9%) than in other fields. Yet, the research intensity of two EET related industries is not meaningfully different than those related to MM. In fact, the research intensity of one EET-related industry sector (aerospace) is relatively high. Several factors may have contributed to the unique results for EET and its related industries. This and other important findings that improve our understanding of sector differences in UIRC commercialisation are further discussed in Section 8.2.3.

7.7: Results for Control Variables

This section discusses the marginal effects and predicted probabilities for each of the control variables in the model.

7.7.1: Researcher Interaction

For every previous OCE-supported UIRC in which a researcher was involved, the predicted probability of a *Startup* increased 1.4 percentage points. This assumed that the rate of increase in the probability was constant for an infinite number of previous UIRCs. Table 7.14 shows the probability of a startup over the range of values for *Researcher Interaction* found within the sample for this study (0-9).

Table 7.14: Predicted Probabilities of a Startup for Researcher Interaction

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Researcher Interaction						
0	0.047	0.009	5.47	0.000	0.030	0.064
1	0.061	0.009	6.68	0.000	0.043	0.079
2	0.078	0.014	5.46	0.000	0.050	0.105
3	0.097	0.024	4.05	0.000	0.050	0.145
4	0.121	0.038	3.19	0.001	0.047	0.195
5	0.148	0.055	2.67	0.008	0.039	0.256
6	0.178	0.076	2.34	0.019	0.029	0.328
7	0.212	0.100	2.13	0.033	0.017	0.408
8	0.250	0.125	1.99	0.046	0.004	0.495
9	0.289	0.152	1.90	0.057	-0.009	0.588

Although the average rate of increase in the probability of *Commercialisation* was 1.4 percentage points when constant over all values, the rate of increase is higher than the average over the range of values found within the sample. Therefore, a researcher with experience in five previous OCE-supported UIRCs is 10.1 percentage points more likely to achieve a *Startup*, compared to a researcher with no UIRC experience.

7.7.2: Gender

Table 7.15 presents the probability of achieving *Commercialisation* based on the researcherǒs *Gender*.

Table 7.15: Predicted Probability of Commercialisation for Gender

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Gender						
Male	0.122	0.012	10.06	0.000	0.099	0.146
Female	0.036	0.024	1.49	0.137	-0.011	0.083

The probability of *Commercialisation* was 8.7 percentage points lower for female researchers compared to male researchers.

7.7.3: Number of Firms

The probability of a *License* increased by 1.4 percentage points for every additional firm involved in the UIRC. However, this assumed that the rate of increase in the probability was constant for an infinite number of firms, which is not realistic. Table 7.16 shows the probability of a *License* over the range of values for *Number of Firms* found within the sample for this study (0-14).

Table 7.16: Predicted Probabilities of a License for Number of Firms

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Number of Firms						
1	0.052	0.008	6.31	0.000	0.036	0.068
2	0.066	0.010	6.76	0.000	0.047	0.085
3	0.082	0.015	5.43	0.000	0.052	0.111
4	0.100	0.024	4.20	0.000	0.053	0.147
5	0.121	0.035	3.41	0.001	0.051	0.190
6	0.144	0.050	2.90	0.004	0.047	0.241
7	0.169	0.066	2.57	0.010	0.040	0.298
8	0.197	0.084	2.34	0.020	0.032	0.362
9	0.226	0.104	2.17	0.030	0.022	0.431
10	0.258	0.125	2.06	0.039	0.013	0.503
11	0.291	0.147	1.98	0.048	0.003	0.579
12	0.326	0.169	1.93	0.054	-0.005	0.657
13	0.362	0.191	1.90	0.058	-0.012	0.736
14	0.399	0.212	1.88	0.060	-0.017	0.814

82.7 percent of the observations in the sample for this study involved one firm, for which the estimated probability of a *License* was 5.2 percent. A further 8.7 percent of the observations involved two firms, while 4.7 percent involved three firms. The predicted probability of a *License* increased from 5.2 percent to 8.2 when the number of firms involved increased from one to two, a difference of three percentage points.

7.7.4: Research per Faculty

The average rate of increase in the probability of *Commercialisation* was 3.3 percentage points for every 100,000 dollar increase in a universityôs expenditures on research and development per faculty member. The actual range of research expenditures per faculty member in the sample for this study was between 1,770 and 360,300 dollars. Figure 7.2 illustrates the probability of technology transfer over this range of values.

The rate of increase was actually higher than average for values of *Research per Faculty* over 250,000 dollars but lower than average for values under 250,000 dollars.

The probability of *Commercialisation* ranged from 6.1 percent for the least research intensive university to 17.1 percent for the most research intensive university in the sample.

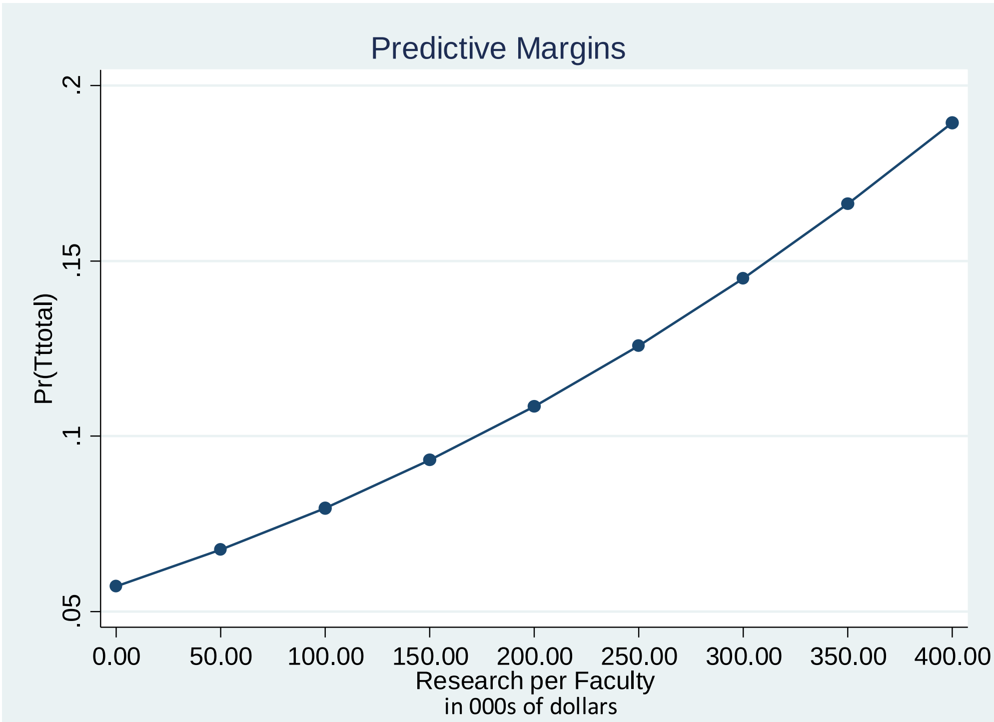

Fig. 7.2: Predicted Margins for Research per Faculty

In the case of a *Startup*, The probability of *Commercialisation* increased by 2.3 percentage points when a universityǿs expenditures on research and development per faculty member increased by 100,000 dollars. Again, this assumed that the rate of increase in the probability was constant for all possible values of the universityǿs expenditures of research and development. Table 7.17 shows the probability of a *Startup* over the range of values found within the sample.

Table 7.17: Predicted Probabilities of a Startup for Research per Faculty

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research per Faculty						
0	0.022	0.010	2.15	0.031	0.002	0.043
50000	0.028	0.010	2.70	0.007	0.008	0.049
100000	0.035	0.010	3.54	0.000	0.016	0.054
150000	0.043	0.009	4.79	0.000	0.026	0.061
200000	0.053	0.009	6.20	0.000	0.036	0.070
250000	0.065	0.010	6.32	0.000	0.045	0.085
300000	0.079	0.015	5.13	0.000	0.049	0.110
350000	0.096	0.024	4.01	0.000	0.049	0.142
400000	0.114	0.035	3.25	0.001	0.045	0.183

The estimated probability of a Startup ranged from 2.4 percent for the least research intensive university to 9.9 percent for the most research intensive university in the sample for this study.

7.7.5: University Operations

In contrast to *Research per Faculty*, an alternative measure of university size, the probability of a *Startup* decreased by 1.3 percentage points for every additional 1,000 dollars in the universityҩs operational budget per full-time student. Table 7.18 illustrates the probability of *Commercialisation* over the range of values for *University Operations* found within the sample for this study.

Table 7.18: Predicted Probabilities of a Startup for University Operations

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
University Operations						
8000	0.092	0.025	3.67	0.000	0.043	0.140
9000	0.074	0.014	5.22	0.000	0.047	0.102
10000	0.060	0.009	6.68	0.000	0.042	0.078
11000	0.048	0.009	5.14	0.000	0.030	0.067
12000	0.038	0.011	3.36	0.001	0.016	0.061
13000	0.030	0.013	2.37	0.018	0.005	0.056
14000	0.024	0.013	1.79	0.073	-0.002	0.050
15000	0.019	0.013	1.43	0.152	-0.007	0.045

The estimated probability of a startup ranged from 2.1 percent for the university with the largest operating budget per student (14,643 dollars) to 8.6 percent for the university with the smallest operating budget per student (8,323 dollars) found within the sample.

7.7.6: Inventions per TTO Staff

For every 10 inventions disclosed annually per technology transfer employee, the probability of *Commercialisation* increased by an average of 3.7 percentage points. However, this rate is constant over an infinite range of values, which is not useful. In the sample for this study, the number of inventions per staff per year ranged from zero to 40. Table 7.19 shows the probability of *Commercialisation* over this range of values.

The probability of *Commercialisation* was higher than average for more than 17 inventions disclosed per technology transfer staff per year, and lower than average for 17 or less.

Table 7.19: Predicted Probabilities of Commercialisation for Inventions per TTO Staff

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Inventions per TTO Staff						
0	0.079	0.014	5.82	0.000	0.052	0.106
5	0.094	0.012	7.93	0.000	0.071	0.117
10	0.111	0.011	10.07	0.000	0.089	0.132
15	0.130	0.013	10.06	0.000	0.105	0.155
20	0.151	0.018	8.29	0.000	0.116	0.187
25	0.175	0.026	6.67	0.000	0.124	0.226
30	0.201	0.036	5.54	0.000	0.130	0.272
35	0.229	0.048	4.79	0.000	0.135	0.323
40	0.259	0.061	4.27	0.000	0.140	0.378

In the case of a *License*, the average probability increased by three percentage points for every increase of 10 inventions disclosed annually for every technology transfer employee. Table 7.20 shows the probability of a *License* over the range of values found within the sample for this study (0-40).

The estimated probability of achieving a license was 5.9 percent for the mean value of inventions disclosed per technology transfer employee per year ($\bar{x}$ = 11.5). The estimated probability of a license ranged from 3.2 percent for the university with the lowest number of invention disclosures to 20.3 percent for the university with the largest number of invention disclosures, a difference of 17.1 percentage points.

Table 7.20: Predicted Probabilities of a License for Inventions per TTO Staff

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Inventions per TTO Staff						
0	0.032	0.008	3.87	0.000	0.016	0.049
5	0.042	0.008	5.28	0.000	0.027	0.058
10	0.055	0.008	6.77	0.000	0.039	0.071
15	0.071	0.010	6.82	0.000	0.050	0.091
20	0.090	0.016	5.63	0.000	0.058	0.121
25	0.112	0.025	4.53	0.000	0.064	0.161
30	0.139	0.037	3.79	0.000	0.067	0.210
35	0.169	0.051	3.30	0.001	0.069	0.269
40	0.203	0.068	2.98	0.003	0.070	0.337

7.7.7: IP Ownership

Table 7.21 presents the predicted probabilities of a *License* for two types of university intellectual property ownership policies.

Table 7.21: Predicted Probabilities of a License for IP Ownership

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
IP Ownership						
University	0.100	0.030	3.30	0.001	0.041	0.160
Creator	0.052	0.009	6.02	0.000	0.035	0.069

The estimated probability of a *License* is 10 percent for universities with university-owned intellectual property ownership policies, compared to 5.2 percent for universities with creator-owned policies, a difference of 4.8 percentage points.

7.7.8: Research Stage

Table 7.22 shows the predicted probabilities of *Commercialisation* at each *Research Stage.*

Table 7.22: Predicted Probabilities of Commercialisation for Research Stage

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Stage						
Earliest	0.152	0.018	8.39	0.000	0.117	0.188
Mid-stage	0.050	0.015	3.34	0.001	0.021	0.080
Latest	0.090	0.047	1.94	0.053	-0.001	0.182

The probability of *Commercialisation* is 15.2 percent for the category *Earliest*, followed by five percent for the category *Mid-stage*, a difference of 10.2 percentage points. The estimated coefficient for the category *Latest* was not statistically significant in the final BNL model.

Table 7.23 shows the predicted probabilities of a *License* at each Research Stage.

Table 7.23: Predicted Probabilities of a License for Research Stage

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Stage						
Earliest	0.084	0.014	6.07	0.000	0.057	0.111
Mid-stage	0.013	0.008	1.68	0.092	-0.002	0.027
Latest	0.068	0.042	1.61	0.107	-0.015	0.151

The probability of a *License* was 8.4 percent for a project at the *Earliest* stage, representing the category with the highest probability of *Commercialisation*. This was followed by the *Latest* stage at 6.8 percent, a difference of 1.6 percentage points. The category *Mid-stage* was not statistically significant for *License* in the final MNL model.

Table 7.24 shows the probabilities of a *Startup* at each *Research Stage*.

Table 7.24: Predicted Probabilities of a Startup for Research Stage

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Research Stage						
Earliest	0.080	0.015	5.27	0.000	0.050	0.110
Mid-stage	0.032	0.012	2.76	0.006	0.009	0.055
Latest	0.021	0.021	0.99	0.321	-0.021	0.063

The *Earliest* stage was once again the category with the highest probability of *Commercialisation* at eight percent. This was followed by the *Mid-stage* stage with a 3.2 percent probability of a Startup. The category *Mid-stage* was not statistically significant for *Startup* in the final MNL model.

7.7.9: Funding per Month

The probability of *Commercialisation* increased by 5.5 percentage points for every additional 10,000 dollars per month awarded by OCE. *Funding per Month* ranges from 229 to 33,380 dollars in the sample for this study. Table 7.25 illustrates the probability of *Commercialisation* over this range of values.

Although the average rate of increase in the probability of *Commercialisation* is 5.5 percentage points when constant over all values, the rate of increase is higher than average over the range of values for *Funding per Month* found within the sample for this study. Within the sample, the estimated probability of *Commercialisation* ranged from 8.6 percent for the smallest amount per month awarded by OCE to 35 percent for the largest amount per month awarded by OCE.

Table 7.25: Predicted Probabilities of Commercialisation for Funding per Month

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Funding per Month						
0	0.085	0.017	5.10	0.000	0.052	0.117
5000	0.110	0.011	9.62	0.000	0.087	0.132
10000	0.140	0.020	7.15	0.000	0.101	0.178
15000	0.175	0.040	4.36	0.000	0.096	0.254
20000	0.216	0.068	3.18	0.001	0.083	0.350
25000	0.263	0.101	2.60	0.009	0.064	0.461
30000	0.314	0.138	2.27	0.023	0.043	0.584
35000	0.368	0.177	2.08	0.037	0.022	0.715

In the case of a *Startup*, every additional 10,000 dollars per month awarded by OCE resulted in a 3.4 percentage point increase in the probability of *Commercialisation*. Table 7.26 illustrates the probability of a *Startup* over the range of values for *Funding per Month* found within the sample for this study (229 - 33,380 dollars).

Table 7.26: Predicted Probabilities of a Startup for Funding per Month

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Funding per Month						
0	0.040	0.011	3.51	0.000	0.018	0.063
5000	0.055	0.009	6.31	0.000	0.038	0.072
10000	0.074	0.016	4.72	0.000	0.043	0.104
15000	0.097	0.034	2.87	0.004	0.031	0.164
20000	0.126	0.061	2.07	0.039	0.006	0.246
25000	0.160	0.096	1.66	0.096	-0.029	0.349
30000	0.200	0.139	1.43	0.151	-0.073	0.472
35000	0.244	0.188	1.30	0.194	-0.124	0.612

The probability of a *Startup* ranged from 4 percent for the smallest award to 22.9 percent for the largest award within the sample.

7.7.10: Distance

With every 100 kilometre increase in distance between the researcher and the lead firm, the probability of a *License* decreased by 0.7 percentage points. This assumed that the rate of decrease in the probability was constant for an infinite range of distances, which is not practical. The range of distances found within the sample for this study was between zero and 7,281 kilometres. Figure 7.3 illustrates the probability of a license over the approximate range of distances found within the sample, on a logarithmic scale.

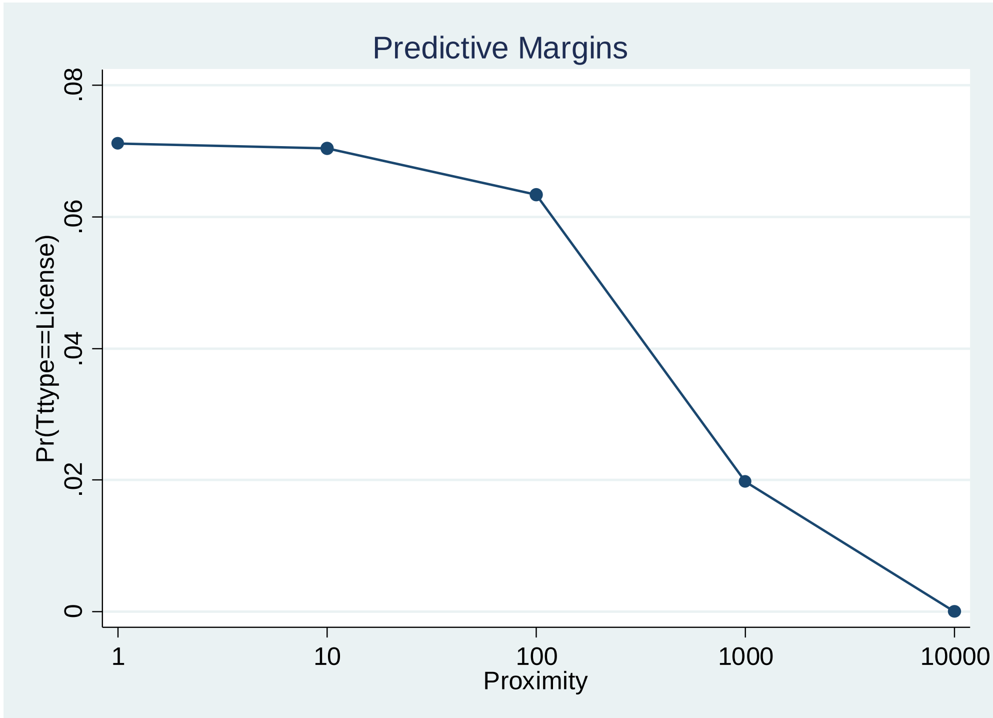

Fig. 7.3: Predicted Margins for Proximity

Table 7.27 shows the probability of a *License* at 100 kilometre intervals up to 1000 kilometres. In the sample for this study, all but 16 observations involved collaborations within 1000 kilometres.

For a UIRC in which the researcher and lead firm were co-located within one kilometre of each other, the probability of a *License* increased by 5.1 percentage points compared to one in which the researcher and the lead firm were 1000 kilometres apart. The rate of decrease in the probability of a *License* slowed at each interval.

Table 7.27: Predicted Probabilities of a License for Proximity

	Margin	SE	z	P>z (95%)	[Conf. Interval]	
Distance						
0	0.071	0.012	6.08	0.000	0.048	0.094
100	0.063	0.009	7.07	0.000	0.046	0.081
200	0.056	0.008	6.71	0.000	0.040	0.073
300	0.050	0.009	5.37	0.000	0.032	0.068
400	0.044	0.011	4.14	0.000	0.023	0.065
500	0.039	0.012	3.26	0.001	0.015	0.062
600	0.034	0.013	2.64	0.008	0.009	0.059
700	0.030	0.013	2.20	0.028	0.003	0.056
800	0.026	0.014	1.88	0.060	-0.001	0.053
900	0.023	0.014	1.63	0.103	-0.005	0.050
1000	0.020	0.014	1.44	0.151	-0.007	0.047

7.8: Results for Various UIRC Scenarios

The study found relationships between commercial outcomes from UIRC projects and several stakeholder characteristic that can be observed *a priori*. This section discusses the predicted probability of different commercial outcomes for both hypothetical UIRC projects and for specific UIRCs found within the sample for this study. These scenarios help to illustrate how granting agencies such as OCE might use this form of predictive modeling to compare different grant proposals with each other, and to help inform their selection processes.

7.8.1: Commercialisation

Based on the studyǿs results, a UIRC project that possessed all the characteristics with the highest estimated probability found within the sample would have a 99.8 percent chance of *Commercialisation*. Specifically, this project would involve:

- a firm that made an in-kind contribution 11 times greater than the government contribution to the project, and
- a researcher in the *Old School*, most likely male, from
- a university that every year conducted over 360,000 dollars in research per faculty and received 40 invention disclosures per technology transfer employee, involving
- research at the *Earliest* stage in the field of *Photonics*, that received
- 33,380 dollars on average per month in funding from OCE.

Not surprisingly, no UIRCs in the sample for this study possessed all these characteristics. The observation in the sample with the highest estimated probability of *Commercialisation* involved:

- a firm that made an in-kind contribution 1.11 times greater than the government contribution to the project, and
- a *Male* researcher in the *Old School*, from
- a university that every year conducted over 291,000 dollars in research per faculty and received 5.1 invention disclosures per technology transfer employee, involving
- research at the *Earliest* stage in the field of *Photonics*, that received
- 16,373 dollars on average per month in funding from OCE.

Based on the characteristics above, the predicted probability of *Commercialisation* of the UIRC was 69.4 percent. The observation in question did indeed achieve *Commercialisation*.

7.8.2: Licenses

Based on the results for the outcome *License*, a UIRC that possessed all the characteristics with the highest probabilities found in the sample for this study would have a 99.9 percent chance of achieving a *License*. Specifically, this project would involve:

- a consortium of 14 firms that made an in-kind contribution 11 times greater than the government contribution to the project, and
- a researcher in the *Old School*, from
- a university with a university-owned intellectual property policy that every year received 40 invention disclosures per full-time technology transfer staff, involving
- research at the *Earliest* stage in the field of *Photonics,* where
- the researcher and the lead firm were located within one kilometer of each other.

Again, no UIRCs in the sample for this study possessed all these characteristics. In contrast to the last example, the observation in the sample with the lowest estimated probability of a *License* involved:

- only one firm that made no in-kind contribution to the project, and
- a *New School* researcher, from
- a university with a creator-owned intellectual property policy that every year received 4 invention disclosures per full-time technology transfer staff, involving
- research at the *Earliest* stage in the field of *Materials and Manufacturing*, where
- the researcher and the lead firm were located 7,281 kilometers from each other.

Based on the characteristics above, the UIRC's predicted probability of a *License* was near zero (5.33E-08). The project did not in fact generate a *License.*

7.8.3: Startups

Based on the results for the outcome *Startup*, a UIRC that possessed all the characteristics with the highest probabilities found in the sample for this study would have an 82.2 percent chance of achieving a *Startup*. Specifically, this project would involve:

- a researcher in the *Old School,* with
- experience on nine previous OCE-supported UIRCs, from
- a university that every year conducted over 360,000 dollars in research per faculty but spent only 8,300 dollars in operating costs per student, involving
- research at the *Earliest* stage in the field of *Photonics*.

Since no UIRCs in the sample for this study possessed all these characteristics, the observation in the sample with the median estimated probability of a *Startup* is described, which involved:

- a *New School* researcher*,* with
- experience on one previous OCE-supported UIRC, from
- a university that every year conducted over 96,300 dollars in research per faculty and spent 8,908 dollars in operating costs per student, involving
- research at the *Mid-stage* stage in the field of *Material and Manufacturing*.

Based on the characteristics above, the UIRCôs predicted probability of a *Startup* was 25.5 percent. The project did not however generate a *Startup*.

This illustrates the potential of the model to run scenarios, better design programs and help funding organisations make better decisions.

7.9: Summary of the Results

Table 7.28: Summary of Results by Independent Variable

	Commer-cialisation	**License**	**Startup**
Hypothesis 1: Embeddedness			
Embeddedness			
Staff	4.3%	N/A	N/A
New School	6.2%	3.0%	2.8%
Rising Stars	11.5%	N/A	N/A
Old School	15.0%	9.1%	6.7%
Laggards	13.6%	N/A	10.7%
Distinguished	11.5%	N/A	N/A
Hypothesis 2: Firm Contribution			
Firm In-kind Ratio	2.6%	2.3%	N/A
Hypothesis 3: Industry Sectors			
Research Field			
CIT	15.5%	10.5%	4.8%
MM	13.0%	5.8%	8.0%
EET	2.9%	1.7%	0.9%
Photonics	26.9%	21.9%	10.2%
Control Variables:			
Researcher Interaction	N/A	N/A	1.4%
Gender			
Male	12.2%	N/A	N/A
Female	3.6%	N/A	N/A
Number of Firms	N/A	1.4%	N/A
Research per Faculty ($100,000s)	3.3%	N/A	0.2%
University Operations ($1,000s)	N/A	N/A	1.3%
Inventions per TTO Staff	0.4%	0.3%	N/A
IP Ownership			
University	N/A	10.0%	N/A
Creator	N/A	5.2%	N/A
Research Stage			
Earliest	15.2%	8.4%	8.0%
Mid-stage	5.0%	N/A	3.2%
Latest	9.0%	6.8%	N/A
Distance (100 kms)	N/A	0.7%	N/A
Funding per Month ($10,000s)	5.5%	N/A	3.4%

The predicted probabilities for the hypotheses related to Embeddedness, Firm Contribution and Industry Sector, and for each of the control variables in the model, are summarised in Table 7.28.

Hypothesis 1 - Embeddedness:

- The results found no evidence in support of Hypothesis 1. In fact, the results suggested the opposite ï greater embeddedness is associated with a greater likelihood of commercialisation
- *Embeddedness* (categories based on position and yrs. since Ph.D.) was a key factor for *Commercialisation*, and for *Licenses* and *Startups* specifically. The category *Old School* (Full Professors with 15+ years since Ph.D.) was category associated with the greatest likelihood of *Commercialisation* and a *License*, but *Laggards* (Mid-level Professors with 15+ years since Ph.D.) were most likely to create a *Startup*.

Hypothesis 2 - Firm Contribution:

- The results for a firmôs cash contribution failed to reject the null hypothesis. However, the results for a firmôs in-kind contribution found evidence in support of the hypothesis that UIRCs with higher contributions from firms are associated with a greater likelihood of commercial outcomes.
- A unit increase in *Firm in-kind Ratio* (ratio of firm in-kind to OCE funding) was associated with an increase the likelihood of both *Commercialisation* and of a *License* by an average of 2.6 and 2.3 percentage points, respectively.

- No firm characteristics (*Firm In-kind Ratio*, *Number of Firms*) were associated with a *Startup*.

Hypothesis 3 – Industry Sector:

- The results found evidence in support of the hypothesis that UIRCs in industry sectors with higher research intensity are associated with a greater likelihood of commercial outcomes.
- *Research Field* was associated with *Commercialisation*, and with a *License* and a *Startup* specifically.
- Photonics was the *Research Field* associated with the greatest likelihood of *Commercialisation* (26.9 percent) and of a *License* and a *Startup* specifically, followed by Communications and Information Technology for a *License* (10.5 percent) and Materials and Manufacturing for a *Startup* (8 percent).

Control Variables:

- *Researcher Interaction* (number of previous OCE-supported UIRCs) was associated with a *Startup*, with an increased likelihood of 1.4 percentage point for each previous project in which a researcher was involved.
- The *Gender* female was 8.6 percentage points less likely to achieve *Commercialisation* compared to male.
- *Number of firms* was positively associated with a *License*, with an increased likelihood of 1.4 percentage points for each additional firm involved in the project.

- Two measures of university size provided contradictory evidence on the relationship between university size and a *Startup*:
    - *Research per Faculty* (research budget divided by number of faculty) was positively associated with the likelihood of a *Startup*
    - *Operations per Student* (operations budget divided by number of students) was negatively associated with the likelihood of a *Startup*
- An increase in 10 *Inventions per TTO Staff* was associated with an average increase in the likelihood of *Commercialisation* of 3.7 percentage points, and in a *License* of 3 percentage points.
- A negative relationship was found between creator-owned *IP Ownership* and a *License*, with creator-owned universities 5.2 percent less likely to generate a *License*.
- *Research Stage* was associated with *Commercialisation*, and with a *License* and a *Startup* specifically.
- With regard to the relationship between *Research Stage* and *Commercialisation*, the likelihood increased successively at each earlier *Research Stage*, except in the case of a *Startup*.
- With regard to *Distance*, greater distance between the researcher and the firm was negatively associated with the likelihood of a *License,* with an average 0.7 percentage point decrease for every additional 100 kilometres in distance between them.
- UIRCs were on average 5.5 percentage points more likely to achieve *Commercialisation* for every additional $10,000 in *Funding per Month*.

CHAPTER VIII: DISCUSSION AND IMPLICATIONS

The implications of the analysis and results from Chapters VI and VII are discussed in the context of the research questions, along with the contribution they make to practice and theory. The limitations of the study's data and models are also outlined.

This study's findings added new evidence on the factors that lead to commercialisation from University-Industry Research Collaborations (UIRCs), and the factors that lead to different types of commercial outcomes. The study also proposed new constructs that extend concepts from related research and, along with the findings, have strong potential to inform the direction of future research on commercial outcomes from UIRCs. In practice, the findings could influence how governments design policies in support of UIRC and how they evaluate specific UIRC project funding applications.

Question 1 probed the stakeholder characteristics that are associated with commercialisation, and explored the extent to which these characteristics contribute to commercial outcomes. *Question 2* examined the stakeholder characteristics associated with either a *License* or a *Startup*, and the extent of their contributions to each type of commercial outcome.

8.1: Introduction

Section 8.2 discusses the results for each of the three hypotheses and the control variables, and their implications on our understanding of commercialisation from UIRCs, and on the specific researcher, firm, university and project characteristics associated with commercial outcomes.

Section 8.3 discusses the policy implications of the study’s findings, and proposes four recommendations to policy makers based on the results.

Section 8.4 describes the contributions of the study to both theory and practice in the fields of university research and development (R&D) and university technology transfer.

Sections 8.5 and 8.6 enumerate the limitations of the data and models used in the study to ensure the appropriate interpretation of the findings.

Finally, Section 8.7 suggests future research that may replicate or build upon the study’s findings.

8.2: Discussion of the Results

The implications of the findings for each of the three hypotheses in this study are discussed below, along with the results for the control variables.

8.2.1: Discussion on Hypothesis 1 - Embeddedness

University researchers play a particularly important role in Canada’s innovation system (Niosi, 2008). Universities represent a significant proportion of total research performed in Canada (Statistics Canada, 2009b), and research grants are generally awarded to researchers rather than to universities. In addition, most Ontario universities have adopted researcher-owned Intellectual Property (IP) ownership policies, which make researchers an even more important stakeholder in Ontario’s university technology transfer system.

The concept of embeddedness is commonly found in the academic literature that seeks to explain how economic behaviour is embedded within social relationships (Granovetter, 1985). Embeddedness has been applied in a number of fields of research to provide useful insight into phenomenon that cannot easily be explained by economic theories alone (Uzzi, 1996). Ambos et al. (2008), the only previous study found to investigate commercial outcomes from UIRCs, used a form of structural embeddedness to evaluate a university researcherøs ñambidexterityò in their response to the inherent tensions between academic and commercialisation activities. Ambos et al. (2008) argued that the greater a researcherøs embeddedness in academic research and its hierarchy, the more their skills, relationships and attitude will be geared toward academic outputs rather than commercial outputs.

Following Ambos et. al (2008), this study hypothesised that commercial outcomes from UIRCs will be negatively associated with researcher embeddedness within academia.

Hypothesis 1: UIRCs involving university researchers who are less embedded within academia will be associated with a higher likelihood of commercial outcomes.

Ambos et al. (2008) measured embeddedness in two ways: 1) using the researcherøs formal rank (i.e. title), and 2) using the number of years spent by the researcher in academia following the completion of their PhD. This study endeavoured to operationalise embeddedness using the same two variables[37]. However, in this case, the two variables

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[37] As described in Section 5.5.2., the measures of the independent variables PhD Age and Position in this study were slightly different than those of Ambos et al. (2008)

were correlated, making it difficult to isolate the independent impact of each variable. Therefore, an interaction technique was applied to the two variables to create six categories of researchers with varying levels of embeddedness. This novel categorisation built upon previous studies in related fields that found evidence of a split between ñnew-schoolò and ñold-schoolò researchers (Owen-Smith and Powell, 2001b), and examined the emergence of ñstar scientistsò who have a high level of all-round achievement in academic and commercial activities (Zucker and Darby, 2001).

The hypothesis tests found that the categorical variable *Embeddedness* was significantly associated with commercial outcomes. However, the results suggested that the directionality of the relationship was opposite to what was hypothesised. Additional hypothesis testing was conducted to investigate the predicted probability of commercialisation for each category of *Embeddedness* to determine the directionality of the relationship. The tests confirmed that more embedded researchers are associated with a higher likelihood of commercial outcomes. The only exception was that *Laggards* (mid-level professors with more than 15 yrs. of research experience) were associated with a greater likelihood of creating startups than the *Old School* (full professors with more than 15 yrs. research experience).

This studyôs findings suggested that more experienced researchers who are more advanced in their academic careers were associated with a higher likelihood to produce commercial outcomes. These findings stand in contrast to those of Ambos et al. (2008) who found that ñprojects with younger, less senior, and higher-cited principal investigators produce the highest proportion of commercial outputsò. However, they are consistent with Leeôs (2000) findings that full professors are more likely to disclose inventions and to patent. Dietz and Bozemanôs (2005) results were mixed, finding that a higher proportion of a researcherôs career spent in industry was negatively associated with publication productivity but positively associated with patent productivity. This studyôs findings may shed further light on the mixed results from previous studies by elucidating the commercialisation behaviour of certain categories of researchers based on their career advancement and experience.

Old School researchers were the top performers overall, and were associated with a predicted probability of commercialisation of 15 percent. To the extent that embeddedness is related to researcher productivity and quality (Gulbrandsen and Smeby, 2005), this studyôs findings are consistent with previous studies on UIRC engagement. Van Looy et al.ôs (2004) study of Belgium and Godin and Gingrasôs (2000)study of Canada found that UIRC engagement does not adversely affect academic productivity, while Perkmann et al. (2013) and Godin (1998) found that higher quality researchers tend to engage more with industry partners.

Interestingly, when broken down by type of outcome, the *Old School* was associated with the highest likelihood of a *License*, but not of a *Startup*. These findings seem to contradict Gulbrandsen and Smeby (2005), who found that researchers involved in a startup published more than those who were not. However, their model revealed that publishing was not significantly associated with startups when controlling for other factors. The relative difference in the *Old School's* performance for licenses compared to startups may be due in part to the fact that startups are a more intensive form of commercialisation. Startups may require more time or energy from the inventor compared to licenses. *Old*

School researchers may not be either willing or able to provide the high level of support required by startups due to the relative importance of their academic responsibilities.

Laggards were associated to the second highest likelihood of commercialisation overall (13.6%), narrowly trailing behind the Old School (15%). However, as described above, *Laggards* were associated with the greatest likelihood of creating a *Startup* of any researcher group, with an estimated probability of 10.7 percent. As with Ambos et al. (2008), this studyøs findings for *Laggards* suggested a negative relationship between generating a startup and academic career advancement. Some *Laggards* may have entered academia later in their career due to previous work within industry, which may have pre-disposed these researchers to pursue industrially-relevant work and to become involved in commercial activity (Dietz and Bozeman, 2005).

Contrary to the discussion above on the role of the *Old School* in startup activity, *Laggards* may have more time to dedicate to startup activity due to having relatively fewer academic responsibilities, or rather; they may not have sufficient time to dedicate towards academic advancement due to their involvement in startup activity. Regardless of the directionality of the relationship, the stronger startup performance of *Laggards* provides insights into the unique nature of startup activity as a commercialisation mechanism.

Taken together, the results for the *Old School* and *Laggards* suggest that older, more experienced researchers have greater commercialisation performance, since both categories include researchers who graduated with their Ph.D. over 14 years ago. Relatively few previous studies have investigated the impact of age and career age on collaboration and technology transfer (Bozeman and Boardman, 2013). The literature on the effects of age have found mixed results: some studies found a positive relationship (Haeussler and

Colyvas, 2011, Link et al., 2007), others found a negative relationship (D'Este and Patel, 2007, Giuliani and Arza, 2009), while others found no evidence of a relationship (Gulbrandsen and Smeby, 2005). However, this studyôs findings on seniority are generally in line with the literature, as described in Section 3.4.2, which has found that seniority is most often positively related to collaboration (Perkmann et al., 2013, Bozeman and Gaughan, 2007, Ponomariov, 2008). Other studies have found no evidence that seniority alone leads to greater UIRC engagement (Ponomariov and Boardman, 2010, Azagra-Caro et al., 2006). As suggested by Boardman et al. (2013), this studyôs findings seem to confirm the extant literatureôs assessment that ñmore experienced researchers are likely to have larger networks, and hence more social capital, enabling them to find potential partners in the private sectorò.

Rising Stars were the third most likely category of researchers associated with commercial outcomes. However, *Rising Stars* ranked only slightly behind *Old School* in their association with the likelihood to generate a *Startup* (6.5% vs. 6.7%, respectively). These results paint a different picture of the young, ambitious and highly ambidextrous researchers described in previous studies (Ambos et al., 2008, Gulbranson, 2008). *Rising Stars* have achieved considerable advancement in their academic position despite their relatively young career age. Their comparatively low performance on commercial outcomes may reflect the need by *Rising Stars* to focus on their academic activities in order to achieve career status as researchers. However, their comparatively better startup performance may indicate a pre-disposition among younger, more career advanced researchers towards startup activity.

Finally, *New School* researchers were consistently associated with the lowest likelihood of generating commercial outcomes by a considerable margin compared to their peers. Although Ambos et al. (2008) found that less embedded researchers were more likely to generate commercial outcomes, they also found that commercialisation was more prevalent among researchers with higher publication citations. Therefore, the relatively low commercialisation performance of *New School* researchers may have been a function of both focus and lack of experience. *New School* researchers may have been more focused on setting their research agenda and pursuing a publication record that would propel them along the tenure track. Ambos et al. (2008) suggested that younger researchers may be more comfortable with industry collaboration and the commercialisation of university research results because they have been trained on the importance of raising research funding from firms, However, the *New School's* relative inexperience and lack of industry networks (Perkmann et al., 2013) may be related to the relatively low commercial outcomes from their UIRCs.

Overall, this studyọs results on embeddedness differ considerably from those of Ambos et al. (2008). The mixed results from these and other previous studies may suggest that the role of researcher embeddedness in commercialisation is highly dependent on the specific structural, cultural, geographic and economic context of the UIRC. Ambos et al.ọs (2008) study used data from 207 UIRCs funded between 1999 and 2003 by the Engineering and Physical Sciences Research Council (EPSRC) in the United Kingdom. Specifically, their sample was from the councilọs ñResponsive Modeò program, which supported high-quality UIRCs in technological fields. The program aimed to fill the middle ground between basic academic research and industry-funded contract research. Based on the information available, Ambos et al.ọs (2008) sample appeared consistent with the sample in this study in terms of stage, field, structure and intent. However, a number of differences may exist between Ontario’s OCE and the U.K.’s EPSRC that are unobserved, yet contribute to the differences in each study’s results.

The differences in the results may also be related to differences between the U.K. and Canadian university systems. The U.K.’s university system is considerably more mature than the Canadian system. The U.K.’s Cambridge and Oxford are among the oldest universities in the world, and the culture of the U.K. system remains grounded in the traditional role of the university in the generation of knowledge and education (Rüegg, 2004). By comparison, the Canadian university system is relatively young. Founded in 1827, the University of Toronto is Ontario’s oldest university. However, the majority of Ontario’s 21 publicly funded universities were established after World War II. In addition, the systems differ in terms of scale and quality. There were 116 public universities in the U.K. in 2008 with enrollment of 2.3 million students (Currie and Standards, 2011). Three of these universities have consistently ranked among the top 10 universities in the world, while only two Ontario universities rank in the top 100 (Consultancy, 2011).

Finally, the differences in the results may be related to the different role that universities play in the U.K. and Canadian national innovation systems. As discussed in Section 2.4., Canadian universities are responsible for a considerably larger proportion of the country’s total expenditures on research compared to the U.K. The predominantly researcher-owned IP ownership policies found at Ontario universities are also in contrast to the U.K.’s predominantly university-owned approach, suggesting an important difference in the respective role of the university and individual researchers in commercialisation activity.

As a result of these differences, this studyôs findings on researcher embeddedness may not be generalisable outside of Ontario or Canada.

8.2.2: Discussion on Hypothesis 2 - Firm Contribution

Research is important to firm productivity and competitiveness (Arrow, 1962); therefore governments subsidise private sector research to improve productivity and competitiveness at a national level. University-industry research collaboration (UIRC) is an increasingly important mechanism of collaboration and technology transfer supported by governments, particularly in Canada (Hanel and St-Pierre, 2006). University researchers receive institutional pressure to raise industry funding to bolster their research budgets. Firms seek to de-risk their research by collaborating and sharing the cost of research with universities, but financial constraints can be a barrier to collaboration (Galán-Muros and Plewa, 2016). Therefore, government subsidies supporting UIRC may increase, or ñcrowd-inò firm research spending by creating financial incentives for collaboration.

The concept of crowding-in/out is widely used in economics to explain either the ñcomplementaryò effect or the ñsubstitutionò effect of government involvement in economic activity (Spencer and Yohe, 1970). There is mounting evidence in the recent academic literature that government subsidies for research collaboration help to stimulate greater private sector research. The type of firm contribution to a UIRC may influence its commercial outcomes. Ambos et al. (2008) stated: ñIt is also conceivable that money provided by the industrial partner may have a different type of effect than more participative forms of collaboration (i.e. the provision of personnel, equipment or facilities). Their study used a dummy variable to indicate whether a cash contribution had been made to the UIRC by the collaborating firm. However, it is conceivable that the amount of firm cash or in-kind contribution may also be associated with its commercial outcomes. Therefore, this study hypothesised that commercial outcomes from UIRCs will be positively associated with higher cash and in-kind contributions by firms.

Hypothesis 2: UIRCs with higher cash and in-kind contributions by firms will be associated with a higher likelihood of commercial outcomes.

Firm cash and in-kind contributions to the UIRCs in the sample were measured as separate variables. However, both variables were correlated with the measure of OCEôs contribution. Therefore, two new scale variables were created to measure the ratio of firm cash and in-kind contributions to OCEôs contribution. The hypothesis tests found that *Firm Cash Ratio* was not significantly associated with commercialisation. However, the results for *Firm In-Kind Ratio* supported Hypothesis 2.

Very few previous studies have investigated firm cash and in-kind contributions separately. Ambos et al. (2008) found no significant association between the type of firm contribution and commercial outcomes. Therefore, this studyôs results stand in contrast to those of Ambos et al. (2008) in finding that firm in-kind contributions are associated with commercialisation. The differences in the findings may be a result of the distinct ways in which cash and in-kind were measured in each study. While Ambos et al. (2008) simply categorised researchers based on the type of firm contribution, this study used a continuous variable that measured the amount of cash and in-kind contributions made firms to each UIRC.

This studyôs findings on firm cash contributions also contrast Gulbrandsen and Smebyôs (2005) findings on industry funding in Norway, which found that ñindustry funding and collaboration are significantly correlated with various types of commercial results, like patents, establishment of new firms, commercial products and consulting agreements.ò The definitions for firm contributions used by Gulbrandsen and Smeby (2005) to categorise groups of researchers may have contributed to the differences between the two studiesô findings. Although Gulbrandsen and Smeby (2005) did not specifically define what was included in their definition of ñindustry fundingò, their studyôs discussion implied that it included only cash contributions. It was unclear how they may have treated in-kind contributions in their researcher categorisation. Therefore, it may not be possible to directly compare Gulbrandsen and Smebyôs (2005) findings and those of this study.

When examining firm contributions by outcome type, this study found that a firmôs in-kind contribution was only a significant predictor of a *License*. In comparison, OôShea et al.ôs (2005) study of U.S. university startup activity found that a higher proportion of research funding by industry was associated with more startups. However, OôShea et al. (2005) measured industry funding in aggregate at the university level, not at the project level. Also, their study did not isolate the independent impact of firm cash and in-kind contributions. Therefore, this studyôs findings shed new light on how different types of firm contributions to a UIRC influence its commercial outcomes.

As discussed in Section 3.5.3 of the literature review, different types of firm contributions are not necessarily considered equal in the eyes of government granting agencies that support UIRCs. This studyôs findings contradict the popular idea among practitioners that ñcash is kingò, implying that a firmôs cash contribution is the best indicator of their commercial interest in the UIRCôs results. However, Gulbrandsen and Smeby (2005) cautioned that research funding may be provided by a firm for a number of reasons and from a number of sources within the firm, including philanthropy or tax incentives. Their study found that ñaround one-third of the 448 professors with industry funding in a 5-year period, did not have regular co-operation with industry colleagues. Conversely, one-third of the 446 professors with regular research collaboration with industry had not received funding from companies in the last 5 yearsò (Gulbrandsen and Smeby, 2005). Indeed, it would seem that cash contributions from firms do not necessarily imply collaboration, and vice-versa. This studyøs results suggest that cash contributions also may not serve as useful indicators of commercial interest in the research outcomes.

The importance of in-kind contributions is often discounted by practitioners as a gauge of commercial interest because they are deemed as ñsoftò, and relatively easier for firms to contribute towards UIRCs. The value of in-kind contributions can be difficult to calculate, and they are also notoriously difficult to track and audit, contributing to why they are viewed with skepticism by government granting agencies. This studyøs findings provide evidence in support of the notion that in-kind contributions capture the effect of informal networks and the accumulation of social capital on commercial outcomes, especially in the case where in-kind contributions take the form of engagement by firm staff (Galán-Muros and Plewa, 2016). Consequently, in-kind contributions may be a greater indicator of interest by the firm in the research problem being addressed, and in the firmøs staff interest to participate in addressing it. The engagement of firm staff may, in turn, be associated with a greater likelihood of licensing. Therefore, this studyøs findings suggest that some types of firm contributions are associated with commercial outcomes, and in-kind contributions in particular are related to commercialisation.

Also discussed in Section 3.5.3 of the literature review was how the level of government subsidy and the amount of firm contribution to a UIRC can vary considerably. Additional hypothesis tests were conducted to determine the effect of different amounts of in-kind contribution on the predicted probability of commercialisation. The likelihood of commercialisation was associated with an average of 2.6 percentage points for every unit increase, while the likelihood of a *License* was associated with an average of 2.3 percentage points for every unit increase. Further analysis of the likelihood of commercialisation over the range of in-kind contributions found within the studyôs sample provided evidence that higher ratios of firm in-kind contribution increased the growth rate in the predicted probability of commercialisation overall, and of the outcome *License* specifically.

Few studies have investigated the impact of the relative size of government subsidies and firm contributions on UIRCs (Zúñiga-Vicente et al., 2014). Aschoffôs (2009) German study found that a minimum subsidy was required to cause a crowding-in of firm research activity. This study found no evidence of such a minimum subsidy effect. Aschoffôs study was not related specifically to UIRC subsidies, and did not consider in-kind contributions made by the firm, which may account for the differences in the results for the two studies. Guellec and Pottelsbergheôs (2003) study of government research subsidies in 17 OECD countries found that the stimulating effect of subsidies increase to a certain threshold, then decreased beyond it. This study found no evidence of a maximum threshold for the effectiveness of UIRC subsidies. In fact, the results indicated that the rate of growth in the likelihood of commercialisation increased as the government subsidy decreased relative to the firm contribution (i.e. as the firm contribution increased). However, this study only investigated the effect of subsidies within the range of values for firm in-kind contributions found within the sample, which may have accounted for the differences in comparison to Guellec and Pottelsbergheôs (2003) results. Therefore, this studyôs findings suggest that greater crowding-in of firm contributions to UIRCs (at least in-kind contributions) are associated with more commercial outcomes.

As described above, this study found that a firmôs in-kind contribution was a significant predictor of a *License*, but was not significant for a *Startup*. Interestingly, none of the firm-related independent variables were significantly associated with the outcome *Startup*. This may have been due in part to the fact that existing firms are not active participants in startup activity. However, they are key stakeholders in licensing activity. In the context of this study, a license was considered an agreement between a firm and a researcher and/or university (depending on the universityôs intellectual property ownership policy) to make use of UIRC results, a relationship in which the firm was generally the key driver. However, the creation of a startup only required action by the researcher and/or the university (again, depending on the universityôs intellectual property ownership policy). This may in part explain why the characteristics of those stakeholders served as better predictors of startups.

This study is among the first to link firm contributions to UIRCs with their commercial outcomes at a project-level. Given the differences between this studyôs results and those of the previous studies in related fields described above, it may be difficult to generalise the findings to government subsidies for private research other than UIRCs. Additional research is required to confirm these results, and to further investigate what specific types of in-kind contributions may be related to UIRC commercialisation.

8.2.3: Discussion on Hypothesis 3 - Research Field

Firms are generally considered the main beneficiaries of university research and development. However, firms with higher levels of expenditure on research and development have a greater absorptive capacity, defined as the firm's ability to value, assimilate, and apply new knowledge (Bierly et al., 2009). The theory of absorptive capacity explains why some firms invest in research even when much of the benefits spill over into the public domain (Cohen and Levinthal, 1990). Absorptive capacity creates a sustainable competitive advantage for firms, and for industries as a whole due to knowledge spillovers.

The research intensity of Canadian firms is lower than the OECD average; it is considerably lower than the U.S. average but slightly above that of the U.K. However, Canada's research intensity in certain emerging knowledge-based industries, such as Information and Communications Technology (ICT) and pharmaceuticals, is on par or higher than that of the U.S. In many traditional manufacturing industries, such as automotive, research intensity is negligible compared to that of the U.S. Therefore, it would appear that important differences in a few key industries can account for a considerable portion of Canada's poor performance on firm research intensity compared to other countries (Iorwerth, 2005).

As predicted by the theory of absorptive capacity, these different industries have adopted unique patterns of engagement with universities in research and commercialisation activities (Perkmann et al., 2013). Several studies in Canada, the U.S. and Europe have found evidence that industry sectors with higher research intensity tend to engage more with universities, and that university commercialisation performance is greater in sectors with high absorptive capacity (Geiger, 2012, Landry et al., 2007b). Building on the absorptive capacity literature, this study hypothesised that commercial outcomes from UIRCs will be more likely in industries with higher research intensity.

Hypothesis 3: UIRCs in industry sectors with higher research intensity will be associated with a higher likelihood of commercial outcomes.

This study measured industry sectors using a categorical variable that recorded which of OCEôs four centres or divisions funded each UIRC project: *Communications and Information Technology* (CIT); Materials and Manufacturing (MM); *Earth and Environmental Technology* (EET); and, *Photonics*. The results of preliminary testing offered support for Hypothesis 3. The categories CIT, MM and *Photonics* were significant and positively associated with commercialisation, relative to the reference category EET. Conversely, Ambos et al. (2008) found no significant relationship between the field of research and commercial outcomes from UIRCs. However, this studyôs findings are consistent with several related studies on technology transfer (Bozeman and Boardman, 2013, Bekkers and Bodas Freitas, 2008, O'Shea et al., 2005).

Additional testing was conducted to determine the predicted probability of commercialisation for each industry sector, and to compare it to each sectorôs research intensity. It was challenging to make a direct comparison between the industry sectors represented by OCEôs four centres and the publicly available information on research intensity by industry in the case of *Photonics* and CIT, since the former is really a sub-sector of the latter. As a result, the two categories were merged into CIT for the purposes of further hypothesis testing, which provided additional evidence in support of Hypothesis 3.

This study's findings suggested that UIRCs in industry sectors with higher research intensity were associated with a higher likelihood of commercial outcomes.

The sub-field of *Photonics* was associated with the highest likelihood of commercial outcomes at 26.9 percent, significantly greater than the rest of the Information and Communications Technology field at 15.5 percent. The results are not surprising given that the application of photonics technology in Ontario was related almost exclusively to fiber optic telecommunications equipment. The industries of Office and Computer Equipment and Radio and Telecommunications Equipment had the highest research intensity of all Canadian industries at 53.63 percent and 27.87 percent, respectively (Iorwerth, 2005). Much of this research was underpinned by Nortel and the related telecommunications cluster in Ontario that supported it. Nortel was Canada's largest technology company, and at one time represented approximately one third of the value of the Toronto Stock Exchange. The effect of this telecommunications behemoth and the cluster it supported can clearly be seen in this study's findings on commercial outcomes from UIRCs.

The field of EET was associated with the lowest likelihood of commercialisation (2.9%) by a considerable margin. Again, not surprisingly, EET is related to some of the industry sectors with the lowest research intensity in Canada, including Basic Metals (1.28%), Other Mining Products (0.29%), and Wood and Paper (0.39%) (Iorwerth, 2005). As previously described in the overview of Canada's national innovation system, primary resource industries exhibit low research intensity not only in Canada, but in most industrialised countries (Nicholson, 2003). Yet, EET was also related to one industry sector with considerable research intensity. The industry sector of Other Transportation, which included the aerospace industry, had the fourth highest research intensity among Canadian industries at 14.48 percent. This industry included Bombardier, one of only three Canadian technology companies on the Fortune Global 500 list of the worldôs largest firms (Niosi, 2008).

There were two reasons why the absorptive capacity of the aerospace industry may not have impacted this studyôs findings. First, Bombardier is headquartered in Montreal, Quebec and most of its Canadian operations are in that province. The geographic location of the company may have affected the level of research collaboration it undertook with Ontario universities. In fact, this study controlled for distance and found that greater distance between the researcher and the firm was negatively associated with the likelihood of a *License* at a rate of 0.7 percentage points for every 100 kilometre increase in distance. Second, the aerospace industry does not collaborate with universities at the same rate as other Canadian industries. As discussed in Section 2.6.1, the Canadian aerospace sector had the second highest percentage of firms that acquired technology licenses (36.8%) from 2002-2004, only slightly behind the pharmaceutical sector (36.9%) (Niosi, 2008). However, no Canadian aerospace firms reported licensing technology from Canadian universities over the same period. Therefore, it is important to consider the unique structure of Canadaôs aerospace industry in the interpretation of this studyôs findings.

The likelihood of commercialisation in the field of MM (12.8%) appeared high relative to the research intensity of its related industries, such as Fabricated Metal Products (1.03%), Motor Vehicles (0.75%), Plastic and Chemicals (1.63%) and Mechanical and Electrical Machinery (2.09%). Again, the reason may lie in the relative importance of universities as a source of external technology within these industries. As was shown in

Table 2.7, the Primary Metal Manufacturing (15.6%), Chemical Manufacturing (12.2%), and Plastics and Rubber Manufacturing (10.4%) industries had the highest proportion of firms that acquired licenses from Canadian universities, with the exception of the Pharmaceutical industry (21.8%). Therefore, the unique patterns of UIRC engagement in each industry are an important moderating factor to be considered in the interpretation of this study's findings.

When examining the results by type of commercial outcome, this study found evidence of a greater probability of licenses than startups in the field of ICT (10.5 percent and 4.8 percent, respectively). This was a surprising result for an industry widely regarded as a hotbed of startup activity due to relatively low product development costs and rapid time to market (Decker et al., 2014). This may have been due in part to Canada's position as a global leader within the telecommunications industry and the preponderance of Canadian telecommunications firms like Nortel. The research intensity of firms in this industry may have increased their receptor capacity for university technology, increasing the likelihood of licenses compared to startups.

This study's findings suggest important industry differences in the likelihood of generating commercial outcomes from UIRCs, and in the likelihood of generating both licenses and startups specifically. The absence of data on UIRCs in life sciences industries was an important limitation of this study that may impact the generalisability of its results. The biotechnology industry is responsible for 50 percent of all university patents, licenses, royalty income and startup activity in Canada and the United States (Mowery and Nelson, 2001). The pharmaceutical industry had the third highest research intensity among Canadian industries. In addition, the pharmaceutical industry had the highest proportion of firms that acquired technology licenses from Canadian universities. Therefore, this studyøs results are most relevant to industry sectors related to engineering and natural, physical and computer sciences.

8.2.4: Discussion on Control Variables Results

Researcher Interaction

The findings suggested a positive relationship between a researcherøs prior interaction with firms through UIRCs and the creation of a *Startup*, which was associated with a five percentage point increase in the likelihood of a *Startup* for researchers previously involved in three UIRCs compared to those previously involved in none. Obviously, researchers who conducted more industrially-relevant research should find it easier to attract more partner firms. Conversely, both Ambos et al. (2008) and Gulbrandsen and Smeby (2005) suggested it was possible that the more collaboration a researcher had with industry, the more industrially-relevant their research pursuits became. Regardless of the directionality of the impact, previous interactions could indeed be considered an indicator of industrial relevance, leading to more success in commercialisation. Ambos et al. (2008) found no relationship between researcher interaction and commercial outcomes and can offer no insights to elucidate these findings.

It was also reasonable to assume that researchers with more previous interactions should have had greater breadth and/or depth of relationships with firms that were potential licensing candidates. In fact, most licenses result from firm leads provided by researchers (Jansen and Dillon, 2000). Yet surprisingly, the findings showed that the number of previous researcher interactions with firms was a significant predictor for a *Startup* but not for a *License*, suggesting a more complex relationship between researcher interaction and commercial outcomes.

Gender

The findings suggested that female researchers are associated with an 8.6 percentage points lover likelihood of commercialisation compared to male researchers. These findings were generally consistent with those of other studies on gender differences in research productivity (Xie and Shauman, 1998), industry engagement (Link et al., 2007) and technology transfer outcomes (Thursby and Thursby, 2005). The extant literature offered few explanations, and unfortunately the findings in this study contributed little to further clarify this phenomenon.

Number of Firms

Interestingly, no firm characteristics were significant predictors for a *Startup*. This may have been due in part to the fact that existing firms are not active participants in startup activity as they are with licensing activity. In the context of this study, a license was considered an agreement between a firm and a researcher and/or university (depending on the universityģs intellectual property ownership policy) to make use of UIRC results, a relationship in which the firm was generally the key driver. However, the creation of a startup only required action by the researcher and/or the university (again, depending on the universityģs intellectual property ownership policy). This may in part explain why the characteristics of those stakeholders better served as predictors of startups.

The study found a positive relationship between the number of firms involved in a UIRC and licensing. The likelihood of a license was associated with a 1.4 percentage points for every additional firm involved in the project. Since no other related studies were found, these represent new insights into the relationship between the number of firms and commercial outcomes from UIRCs. The number of firms involved may have served as a gauge of general industry interest in the research problem being addressed, hence the association with a greater likelihood of the results being licensed. More practically, the involvement of more firms in a UIRC may have been due to the fact that there were more licensing candidates with intimate knowledge of the research and its results.

University Size

Generalised multicollinearity was detected between a universityǿs reputation, size and technology transfer operations. This was a complicating factor in the development of the research model for this study and has implications for future research involving alternative measures of university characteristics. It would be reasonable to presume that certain university characteristics would serve as predictors of both licenses and startups. Yet, the study found that the university characteristics that were associated with a *License* were entirely different than those associated with a *Startup*, with no commonality between the two.

The study found a relationship between university size and the creation of startups. Interestingly, two different measures of university size provided contradictory evidence on the directionality of this relationship. Larger research budgets per faculty member were positively associated with a *Startup*, with an average increase in the likelihood of 2.3 percentage points for every 100,000 dollar increase in research expenditures per faculty member. However, larger operational budgets per student were negatively associated with a *Startup*, with an average decrease in the likelihood of a startup of 1.3 percentage points for every 1,000 dollar increase in the operational budget per student. These findings suggested that research intensity was an important fuel for university startup activity, and support the conclusion by O'Shea et al. (2005) that an increase in the funding base in science and engineering would lead to an increase in startup activity. In contrast, operationally intensive universities may have reinforced a more bureaucratic culture that stymied startup activity.

The findings also suggested a relationship between a universityĝs size, measured using *Research per Faculty*, and the years of experience of its technology transfer office. Indeed, it seems reasonable for more research intensive institutions to have a longer track record of technology transfer activities.

Inventions per TTO Staff

The study found a positive relationship between commercialisation and the number of inventions disclosed per TTO staff, with an average increase of 3.7 percentage points for every 10 additional inventions disclosed per TTO staff. However, when broken down by type of outcome, invention disclosures were only a significant predictor of licenses. The relationship between *License* and *Inventions per TTO Staff* suggested a three percentage points increase in the likelihood of a license for every increase of 10 inventions disclosed per TTO staff. This stood in contrast to González-Pernía et al. (2013) and O'Shea et al. (2005), who found a positive relationship between TTO size and startups. Yet, it seemed logical that universities with more invention disclosures would generate more licenses, since inventions were the raw materials packaged by technology transfer offices into licensable properties. In fact, invention disclosures were tools created by technology transfer offices to unearth these raw materials. Therefore, technology transfer offices were designed to be licensing machines rather than startup factories by their very nature. Consequently, this studyǿs findings suggested that more inventive universities would generally have more sophisticated TTOs, which according to Siegel et al. (2004) leads to more licenses.

Intellectual Property Ownership

The study found a negative relationship between creator-owned intellectual property policies and licenses. The results suggested that a *License* is 4.8 percent less likely at universities with creator-owned policies. Creator-owned policies may indeed represent a form of incentive, and greater incentives should lead to greater commercial outcomes (Lach and Schankerman, 2004). However, this studyǿs results suggest that the associated reduction in the universityǿs incentive to pursue licensing may be greater. This might lead to the presumption that creator-ownership would instead encourage startup activity, but the studyǿs findings offered no evidence in its support.

Research Stage

Interestingly, the study found that earlier stage projects were associated with a greater likelihood of commercialisation, with projects at the *Earliest* stage associated with a 15.2 percent likelihood of success. This was contrary to the popular belief among practitioners that later stage UIRCs had a greater likelihood of commercialisation because they were ñcloser to marketò. Yet, the studyǿs findings support those of Gulbrandsen and Smeby (2005) that basic research generates more commercial outcomes than applied research. The results suggested that the likelihood of a startup increased successively at each earlier stage. However, projects at the *Earliest* stage were associated with an 8.4 percent chance of a startup, followed by the *Latest* stage at 6.8 percent. No explanation for these findings was evident and therefore, the results for research stage should be interpreted with caution.

Project Size and Length

The measures of UIRC *Size* and *Length* were combined into a relative measure of *Funding per Month*. Predictably, the study found that UIRCs that received 10,000 dollars per month more in funding were on average associated with a 5.5 percentage point greater likelihood of commercialisation. Although Ambos et al. (2008) found no relationship between size and duration and commercial outcomes, the results from this study appear to suggest that the intensity of the UIRCs is associated with commercial outcomes. *Funding per Month* was associated with startups but not licenses, and the potential reasons for this difference remain unclear.

Distance

Not surprisingly, the study found that greater distance between the partners was associated with a decrease in the likelihood of a license by 0.7 percentage points for every 100 kilometre increase in distance. These findings support the supposition by Agrawal and Cockburn (2003) that face-to-face interaction between UIRC partners is important to the transfer of tacit knowledge which may be more difficult and less frequent with increased distance.

8.3: Policy Implications

This study considered the relationship between important UIRC stakeholder characteristics and commercial outcomes from UIRC, based on the results from previous academic studies and the unique composition of Canadaös national innovation system. The study found evidence that characteristics related to each UIRC stakeholder: researchers; firms; universities; and, government programs that support UIRC; were strongly associated with commercialisation.

The findings suggest that government granting agencies that adopt policies that consider characteristics of all stakeholders have the opportunity to generate greater commercialisation outcomes than those rooted in the perspective of a single stakeholder. For example, certain granting agencies that are more research-oriented or commercialisation-oriented in their approach to UIRCs may tend to develop processes and criteria that are more heavily weighted in favour of either researchers or firms. Indeed, it would seem that maximising the potential for UIRC commercialisation requires a balanced approach that considers the perspective of all stakeholders.

Therefore, this study offers four recommendations to policy makers and government granting agencies in Canada based on its findings; one recommendation related to each of the four stakeholders in UIRC.

8.3.1: Recommendation 1 – Nurture Embedded Researchers

This study found strong evidence that more embedded researchers are associated with a greater likelihood of generating commercial outcomes from UIRCs. As a result:

It is recommended that policy makers develop awareness and education programs that encourage older, more career advanced and high-quality researchers to become involved in UIRC and commercialisation.

Such programs could take many forms. An exemplary program from the United States is the National Science Foundationôs Innovation Corps (i-Corps) program. Built upon lean startup principles (Ries, 2011), the program ñprepares scientists and engineers to extend their focus beyond the university laboratory, and accelerates the economic and societal benefits of NSF-funded, basic-research projects that are ready to move toward commercializationò (National Science Foundation, 2017). A smaller scale Canadian program with a similar intent is the University of Toronto Impact Centreôs Techno program, ñan elite entrepreneurship training program for the top science and engineering students and recent graduates who want to create high-impact technology-based startupsò (Impact Centre, 2017). Although designed for elite students and graduates, a program like Techno could be modified to meet the needs of highly embedded researchers.

Programs such as these could target more embedded researchers in particular, but need not necessarily ignore or exclude other categories of researchers. Changing the entrepreneurial culture of all researchers, including younger, less embedded researchers, should remain an important policy objective. However, the findings suggest that awareness and education programs targeting younger researchers would pay off in the long run, but changing the culture of embedded researchers could pay off in the shorter term.

8.3.2: Recommendation 2 – Encourage In-Kind Contributions

This study found strong evidence that greater in-kind contributions from firms to UIRCs are associated with a higher likelihood of commercial outcomes. Therefore:

> **It is recommended that in-kind contributions by firms should not be discounted in the selection criteria used by government granting agencies.**

Many granting agencies prefer cash contributions by firms in the belief that they represent a stronger commitment by the firm to the project, and by extension, a stronger indication of the firmøs intent to commercialise its results. Conversely, in-kind contributions are often viewed by granting agencies as ñsoftò money that can be difficult to quantify, and therefore prone to overestimation. In-kind contributions are also notoriously difficult for granting agencies to track and audit. In the case of some programs, in-kind contributions may not even be recognised by granting agencies.

This studyøs findings suggest that the concerns of some granting agencies regarding the legitimacy of in-kind contributions may not be founded. It is possible that certain types of in-kind contributions are preferable to others. For example, contributions of firm staff time may indicate a greater level of engagement or collaboration, which may in turn be associated with a greater likelihood by the firm to commercialise UIRC results. Although this may be a reasonable assumption, this study did not distinguish the impact of different types of in-kind contributions on commercialisation.

8.3.3: Recommendation 3 – Concentrate on Large Universities

In 2010, university research represented 36.8 percent of all research and development expenditures in Canada, a share that has been increasing steadily since 1997 (Niosi, 2008). In fact, Canada was second among OECD countries in terms of expenditures on university research as a percentage of its GDP. However, there is considerable disparity in the scale of the research activity, commercialisation output and reputation of Ontario's universities. This study found that a university's size, in terms of research dollars per faculty member, was strongly related to commercialisation. Therefore:

> **It is recommended that policy makers concentrate on developing world class research capabilities and commercialisation infrastructure at a small number of large universities.**

Concentrating research and commercialisation efforts at a relatively small number of large universities that are already responsible for the majority of commercial outcomes will focus energy, talent and resources in a way that further develops the commercialisation capacity of these institutions to a world-class level. In 2010, only two universities in Ontario ranked within the top 100 universities in the world by research (Times Higher Education, 2011). The University of Toronto was the largest research university in Ontario by a significant margin, representing 35 percent of all university research in the province in 2010. The University of Toronto's CDN$878.4 million in sponsored research was more than double that of McMaster University, Ontario's second largest with CDN$395.4 million in sponsored research. The University of Toronto is the only university with research capacity large enough to compete with the world's largest and most prestigious universities.

In a world where universities increasingly compete globally for talent, industry engagement, and investment in commercial outcomes, size matters. This study found that university size and reputation were correlated, suggesting a halo effect in which university size, reputation and commercialisation are inter-related to create a virtuous cycle (Baldini, 2006). In 2004, the top 25 research universities in Canada accounted for 95 percent of all licensing royalties and 78 percent of all startups (Niosi, 2008). Government policies should direct a greater proportion of research funding and commercialisation support to a small group of research universities to re-inforce this halo effect, and to help more Canadian universities grow to become world-class institutions. This group of elite universities would be similar to the Russell group of 24 research-intensive, world-class universities in the U.K. Indeed, Canadaȏs U15 group of top research universities are responsible for 80 percent of all sponsored university research in the country and represents an ideal place to start. Improving the performance of these elite universities will involve not only redoubling their research efforts, but also considerable investment in enhanced commercialisation capacity, including better incentives for UIRC, larger technology transfer offices, campus-based startup incubators, and university sponsored investment funds.

8.3.4: Recommendation 4 – Focus on Research Intensive Industries

Traditionally, Canada has invested considerably less in research and development than the OECD average. Canadaȏs weak research performance is largely attributable to low research activity by firms (Iowerth, 2005). In turn, there are major differences in the research intensity of different industries that account for a significant portion of Canadaȏs comparatively weak performance. This study found a positive associate between commercial outcomes from UIRC and industry sectors with high research intensity. Therefore:

It is recommended that governments and granting agencies focus on supporting research collaboration between universities and the most research intensive industries to maximise the likelihood of commercialisation.

Other than primary resource industries, which have low research intensity across most industrialised economies, the least research intensive industries in Canada are traditional manufacturing-based industries. These industries have been in decline since the 1980s due largely to lower production prices caused by global competition. A number of policy initiatives have attempted to curb the decline in these manufacturing industries, with limited success. This studyǿs findings suggested that policies to encourage UIRC in these low research intensive industries would fare no better.

The most research intensive industries in Canada are high-growth technology sectors such as Information and Communications Technology (ICT) and biotechnology. This further underscores the transition in the Canadian economy from traditional manufacturing industries to knowledge-based industries. This studyǿs findings suggest that commercial outcomes from UIRCs are most likely in the ICT sector. Although this study did not include data from UIRCs in the biotechnology industry, previous studies have found that biotechnology accounted for approximately half of university commercialisation in the U.S. and in Canada (Mowery and Nelson, 2001).

Canadian industries with high research intensity that do not frequently use universities as a source of external technology may be particularly ripe for policy intervention. For example, the Canadian aerospace industry has high research intensity, and 36.8 percent of firms in that industry acquired licenses from external sources between 2002-2004 (Niosi, 2008). However, none of these firms acquired licenses from Canadian universities. Government policies that promote universities as sources of technology, and subsidy programs that incentivise UIRC within these sectors may pay particularly high dividends.

8.4: Contribution of the Study

The studyôs findings constituted important contributions to both theory and practice. They have implications that could influence the direction of future research on UIRCs and the commercialisation of their results. The findings could also influence how government granting agencies that support UIRCs design their funding programs and/or evaluate funding applications.

8.4.1: Contribution to Theory

UIRCs have been understudied because of the nascent stage of research in academic entrepreneurship in general, and because of limited access to reliable data on UIRCs in particular. Consequently, the novel dataset created for the purpose of this study represents in and of itself a contribution to this field of research. The dataset was assembled manually from disparate proprietary and public sources, and thereby offered several new insights on the potential to predict UIRC commercialisation that would not have otherwise been possible.

As described in the literature review, most previous studies on UIRCs were focused on the effect of collaboration in generating knowledge, while most of the extant technology transfer literature was focused on the factors associated with commercialising invention disclosures. This study made a number of meaningful contributions to our understanding of formal UIRCs as a mechanism for early-stage commercialisation, therefore bridging the gap between these two fields of literature.

This studyôs findings built upon those of previous studies that found mixed results on the relationship between a researcherôs embeddedness in academia and the commercial outcomes of UIRCs. This study confirmed that embeddedness factors such as career age and seniority are indeed related to commercial outcomes, but not in the way that was hypothesised in this study, following Ambos et. al (2008). The finding that researcher embeddedness is positively associated with commercialisation in Ontario is an important new insight, and suggests that additional work is needed to further our understanding of how contextual factors contribute to the divergent results in different innovation systems.

This study proposed a novel categorisation of researchers based on their level of embeddedness. The approach built upon previous studies that identified a split between ñnew schoolò and ñold schoolò researchers, and identified ñstar scientistsò with a high level of overall achievement. This categorisation scheme holds promise as an alternative measure of embeddedness for future research and as a useful tool that can be adopted by practitioners.

The studyôs findings on embeddedness suggest that startup activity is somehow unique as a commercialisation mechanism, as are the researchers involved in startup activity. A particularly interesting result worthy of further study is the role of ñlaggardò researchers in startup activity. Additional research is required to better understand the factors that lead some researchers to choose one mechanism over the other.

This studyøs findings on firm contributions to UIRCs contribute to the growing body of literature that suggests government subsidies have the effect of ñcrowding-inò private sector research expenditures. This study is among the first project-level studies to link firm contributions to the commercial outcomes of UIRCs. However, this study only found evidence that in-kind contributions were related to commercialisation. Another important finding was that the relationship between in-kind contributions and commercialisation was not linear; more crowding-in of firm in-kind contributions increased the growth rate in the likelihood of commercialisation.

The findings on firm contributions were only significant for licenses, and not for startups. Interestingly, no firm-related variables were associated with startups, which contributed further evidence regarding the important differences between licenses and startups as commercialisation mechanisms that need to be better understood.

This studyøs findings on industry differences in UIRC commercialisation in Ontario contribute to the existing literature that suggested research intensity increases the absorptive capacity of firms. The studyøs findings confirmed that commercial outcomes from UIRCs were positively associated with industries that have higher research intensity. However, the role of research intensity was moderated by the extent to which universities serve as a source of external technology in each industry, which is unique to the Canadian context of this study. The studyøs findings also suggested that licensing was more popular than startups in ICT, possibly due to the particularly high receptor capacity of Canadian firms in that industry. Additional work on sectoral differences in licensing and startup activity in other innovation systems is needed to investigate the extent to which this studyøs results are generalisable to comparable industry sectors outside of Canada.

8.4.2: Contribution to Practice

This study provided new insights on the factors associated with UIRC commercialisation. The findings could be useful to university technology transfer offices, government granting agencies that support UIRC, and other practitioners in a number of ways.

First, this studyøs findings could be used by government granting agencies to design new UIRC support programs or modify existing programs to become more effective at generating commercial outcomes. The findings on the importance of firm in-kind contributions to UIRC could encourage granting agencies to set or increase minimum contribution levels by firms. Program criteria could also be modified to give greater consideration to in-kind contributions rather than the preference for cash contributions that exists in many programs. The findings on sector differences in commercial outcomes from UIRC could also be used by granting agencies to set specific criteria for UIRC projects in each industry, based on the unique patterns of university-industry engagement in each sector. In addition, this studyøs findings on the unique factors associated respectively with licenses and startups could be used by granting agencies to develop programs that target a particular type of commercialisation.

Second, this studyøs findings could be used by granting agencies to improve their selection process and to make funding decisions that maximise the likelihood of commercialisation from UIRCs. The study found evidence that greater researcher embeddedness is associated with greater commercial outcomes. The findings from previous studies also suggested that embeddedness may be related in part to researcher quality. Measuring researcher quality using the methods commonly employed by academic researchers, such as publication citations, is not practical for use by granting agencies in making funding decisions, or by Technology Transfer Offices (TTOs) in determining which researchers to support in their commercialisation efforts. The six categories of researcher embeddedness proposed in this study could serve as a crude but useful tool for granting agencies and TTOs to quickly profile researcher embeddedness and quality, and make better decisions on the allocation of resources.

8.5: Limitations of the Data

The studyǿs data has a number of limitations that should be considered carefully when interpreting its findings.

8.5.1: Use of secondary data

The study relied primarily on the accuracy and validity of input data reported by applicants to OCEǿs UIRC support programs, and of outcome data collected by OCE staff. OCE committed staff resources to assist in the collection and review of data for accuracy prior to its use in the study. In addition, comprehensive data collection and descriptive analysis procedures were undertaken, as described in Chapter III. This served to mitigate the risk of data entry error and contributed to making the data as accurate as possible given the constraints.

8.5.2: University Characteristics

The independent variables used to measure university characteristics varied across universities. However, the data did not vary over time due to challenges in availability of data for the time horizon of this study. Consequently, these independent variables may simply have picked-up university fixed-effects rather than the impact of the characteristic being measured. As a result, the results on university characteristics should be interpreted with caution.

8.5.3: Representativeness

The sample was selected based on the criteria outlined in the sampling procedures section. In the case of the MNL model, 19 observations were excluded to avoid perfect prediction. Given the relatively small number, these observations were visually inspected to detect any similarities or patterns. It was determined that the excluded observations were random in nature and did not affect the representativeness of the sample.

One particular issue that was considered closely was the potential bias of the sample based on the age of the observations. The sample for this study includes observations from 2000 to 2009, but the sample is skewed slightly towards newer observations. This study aimed to predict commercialisation as a guide for future decision-making. Newer projects are more likely to reflect the present environment. Hence, such a bias may in fact make the studyôs findings more relevant and current.

8.5.4: Content Validity

The set of variables included in the model was developed based on the extant literature and suggestions from practitioners in the field. Although the list was meant to be as comprehensive as possible, some variables deemed to be important in the literature including Researcher Quality and Firm Openness, were not included because data was not available. In addition to those mentioned above, other characteristics, which are either unobserved in the model or unobservable, could influence UIRC commercialisation.

8.5.5: External Validity

The nature of the data provided by OCE affects the external validity of the study's findings in four ways. First, OCE supports UIRCs primarily in the fields of engineering, and physical and applied sciences, generally excluding natural and life sciences, as well as medical research. Yet, life sciences and medical research contribute more towards university technology transfer activity in the U.S. than any other field (Thursby et al., 2001, Thursby and Kemp, 2002). Although this may limit the generalisability of the findings beyond OCE's narrow fields of interest, they shed light on these less understood fields, since most technology transfer research is based on life sciences and pharmaceuticals data.

Second, OCE only supports UIRCs within Ontario universities. This geographic limitation is mitigated by the fact that OCE projects are representatively distributed within all of Ontario's universities, which include small regional schools as well as some of the most well respected research institutions in the world.

Third, OCE only supports formal UIRCs in which the collaborating firm(s) must make some form of cash or in-kind contribution to the project and agree to be party to a standardised Research Collaboration Agreement (RCA). This may limit the generalisability of the findings to similar types of formal UIRC.

Finally, the UIRCs in the study's sample had already been vetted by OCE using a peer review process. The formal selection criteria used by peer reviewers was different for each of OCE's UIRC support programs and may have evolved slightly over time. The peer reviewers used in the process also changed over time, which may have introduced variability in how the selection criteria were applied by different individuals.

8.6: Limitations of the Model

The model used in this study also has a number of limitations that should be considered carefully when interpreting its findings.

8.6.1: Omitted Variable Bias

The models in this study did not include measures of researcher productivity and quality. Based on the findings from the extant literature, the absence of researcher productivity or quality measures created the potential for omitted variable bias. Econometric testing for omitted variable bias was conducted. This included fixed-effects regressions at the researcher level that attempted to remove potential omitted variable by adjusting for intra-group variation that is not explained by the independent variables. Unfortunately, the results of the researcher fixed-effects regressions were problematic, and therefore not effective in removing bias created by the omission of potentially relevant researcher variables. Some of the variables included in the model, such as those related to embeddedness and university size, were likely to be highly correlated with researcher productivity and quality. This may serve as a mitigating factor. Despite the various attempts to limit the risk of omitted variable bias, it remains a limitation of this study.

8.6.2: Delimitations of Dependent Variables

The models in this study measured only two types of commercial outcomes; licenses and startup companies. This does not discount the importance of other types of outcomes stemming from UIRCs, such as training, jobs and informal linkages. However, licensing and startups represent two of the most tangible commercial outcomes, and are the only outcomes data that OCE has collected consistently since 2000. Also, following

Bozemanǿs (2000) ñout-the-doorò criterion for successful technology transfer, the study measured only whether or not a license or startup occurred, with no consideration of its impact. Several exogenous factors can contribute to such impacts. Using this criterion avoids the problem of attributing these impacts to the UIRC versus other factors that are outside the scope of the collaboration or outside of the stakeholdersô control.

8.6.3: Internal Validity

The research questions explored the relationship between the commercialisation of UIRC project results and certain characteristics that can be observed *a priori*. Several *a posteriori* factors, such as potential changes in the relationship between the stakeholders, project management effectiveness and market fluctuations, were extraneous to the research design but may nevertheless influence UIRC commercialisation. Two important design features mitigated the influence of such extraneous factors on the model and helped to establish internal validity. First, a comprehensive set of independent variables was included in the model to control for as many factors as was practicable. Second, the constraints imposed by OCEǿs evaluation process, project structure and standardised RCA provided an additional form of control.

8.6.4: Construct Validity

Construct validity was established by employing as many measures, instruments and constructs as possible from related theory and literature. In some cases, constructs were operationalised using alternative approaches either in response to the limitations created by the available data or to better reflect the context of the study. For example, this study employed modified constructs to measure R&D intensity, project stage, interaction and researcher seniority. The use of these alternative approaches was considered when interpreting the studyôs findings.

8.6.5: Cross-sectional Time-Series Research Design

The studyôs research design measured the characteristics of stakeholders prior to the start of the UIRC as well as outcomes that occurred by the end of the data collection phase. Contrary to the sample selection bias towards newer observations discussed in the representativeness section, the cross-sectional time-series research design presented a potential bias towards older observations. Because data was collected from historical records on projects that occurred up to 2009, a greater proportion of older projects may have been recorded as successful simply because they had more time to generate commercial outcomes. However, this factor is not relevant to the model because none of the research questions deal with how long UIRCs take to achieve successful outcomes.

Nevertheless, it must be acknowledged that successful commercialisation can take many years. The need to set an arbitrary cut-off date in the sample selection criteria implies that projects were recorded as failures if they had not yet generated a commercial outcome. Some of these projects may nonetheless generate a commercial outcome in the fullness of time.

8.6.6: Objectivity

I have worked for OCE as both an employee and as a consultant since January 2000. I have held various roles within the organisation such as Manager of Business Development, Director of Commercialisation and I am currently the Director of Academic Entrepreneurship. I was also previously the Director of OCEôs Accelerator Program, a program that invested in university-based startup companies. As a consultant to OCE, I assisted in due diligence on projects, worked with OCE-supported startup companies, and advised on the design and implementation of various programs. Notwithstanding my professional relationship with OCE, the organisation is providing me no compensation, financial or otherwise, in consideration for conducting the study.

8.6.7: Reliability

The majority of data for this study was taken from historical records, which contribute to the consistency and the repeatability of the measurements. However, there are some exceptions that should be noted. The measures of *Firm Size* required estimation by OCE staff based on instructions provided to them, in cases where sufficient data was not available in OCEǿs historical records. The interpretation of these instructions may have varied between staff and affected the reliability of these measures.

8.7: Future Research

Additional research is required to further the understanding of UIRCs as a mechanism for commercialising university technology. Replication research using a similar model with data from a different jurisdiction would contribute towards testing the external validity of the studyǿs findings. Such a study would improve our comprehension of the significance and impact of important factors, especially new constructs such as the proposed researcher embeddedness categories, and the extent to which they are generalisable beyond the specific data set and jurisdiction used in this study.

The finding that the proposed operationalization of researcher embeddedness is positively associated with commercialisation in Ontario is an important contribution of this study, but does suggest that additional work is needed to further our understanding of how contextual factors contribute to the divergent results on embeddedness in different innovation systems. Additional research is also required to better understand the factors that lead researchers with different levels of embeddedness to choose one mechanism over another.

Alternatively, similar research using different or additional independent variables could help further refine the most appropriate specification for modeling UIRC commercialisation. In particular, adding one or more measures of researcher characteristics, including quality, could help reveal the extent to which the model in this study suffers from omitted variable bias.

Similar research using a different or an expanded definition of commercialisation would help further the studyǿs findings on the factors that affect different types of UIRC outcomes. Additional or alternative types of commercial outcomes might include the training of highly qualified people, job creation including hiring by the firm(s) as a result of the UIRC, technology made available through open sources and in the public domain, and other measures of economic development or market impact.

Similar research on other formal and informal types of research collaboration would help further the studyǿs findings on how the structure of the collaboration affects commercialisation. The definition of collaboration used in this study was relatively strict based on the structure of OCEǿs UIRC support programs. However, research collaboration between the stakeholders identified in this study could take many alternative forms, including contract research, internships and fellowships, firm sponsorship or investment in university equipment and infrastructure, and the secondment of academic researchers to firms.

This studyǿs findings suggest that the concerns of some granting agencies regarding the legitimacy of in-kind contributions may not be founded. It is possible that certain types of in-kind contributions are preferable to others. For example, contributions of firm staff time may indicate a greater level of engagement or collaboration, which may in turn lead to a greater likelihood by the firm to commercialise UIRC results. Although this may be a reasonable assumption, additional research is needed on the potential impact of different types of in-kind contributions on commercialisation.

Finally, similar research comparing the commercialisation of UIRC results within alternative fields of research could improve our understanding of the generalisability of the studyǿs results beyond physical sciences and engineering, to include fields such as natural and life sciences, as well as medical research, which account for the majority of university technology transfer activity.

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APPENDIX A – DATA USE AGREEMENT

Data Use Agreement

This Data Use Agreement ("Agreement") is effective as of the 1st day of April, 2011 ("Effective Date") and is made

BETWEEN:

> **ONTARIO CENTRES OF EXCELLENCE INC.**, a corporation incorporated and existing under the laws of Ontario and having its principal place of business at 156 Front Street West, Suite 200, Toronto, Ontario, M5J 2L6 (hereinafter "OCE"),

AND

> **MARTIN CROTEAU**, an individual residing at 275 Stover Cres., Pickering, Ontario, L1V 6R1 (hereinafter the "Researcher"), Doctoral Candidate and Research Associate at the Henley Business School, University of Reading (hereinafter the "University"),

WHEREAS the parties entered into a Confidentiality Agreement on December 16, 2009 to provide the Researcher with certain information to develop a research proposal for submission to OCE;

AND WHEREAS the Researcher has submitted a Research Proposal (hereinafter the "Project") to OCE as attached in Appendix 1.

AND WHEREAS OCE has agreed to disclose confidential information to the Researcher for the purpose of conducting academic research as outlined in the Project,

NOW THEREFORE in consideration of the premises and the mutual covenants herein and other good and valuable consideration (the receipt and sufficiency of which is hereby acknowledged by each of the parties) the parties hereto covenant and agree as follows:

ARTICLE 1: DEFINITION OF CONFIDENTIAL INFORMATION

1.1 For the purposes of this Agreement, the term "**Confidential Information**" means any information and any fields or variables derived from this information, which is non-public, confidential or proprietary in nature, including, without limitation, business information, trade secrets, know-how, and any other information related to OCE's business, which is disclosed by or on behalf of OCE to the Researcher, whether before or after the Effective Date, on whatever media it shall exist, whether written, oral or in electronic form, but shall not include information that:

(a) is or becomes generally available to the public through no fault of the Researcher;

(b) is rightfully received from a third party without similar restriction or without breach of this Agreement;
(c) the Researcher is able to demonstrate, in writing, was known to it on a non confidential basis before such information was disclosed; or
(d) was independently developed

1.2 All Confidential Information provided by OCE is provided "as is" and OCE makes no warranties, whether express, implied or statutory, regarding the Confidential Information, including, without limitation, as to its accuracy, completeness, sufficiency, merchantability, fitness for a particular purpose or non-infringement, unless such warranties and/or representations are specifically set out in writing by OCE, addressed to the Research and delivered to the Researcher as such.

ARTICLE 2: USE OR DISCLOSURE

2.1 The Researcher shall have the right to use and disclose Confidential Information provided to it by OCE for research purposes as described in the Project and for no other purpose, subject to the restrictions in Article 3 below.

2.2 The use and disclosure of Confidential Information will be consistent with the policies set out by the University's Research Ethics Committee.

2.3 Confidential Information may be disclosed to the Researcher's academic supervisors at the University, who shall be advised of the terms of this Agreement and the restrictions upon use and disclosure of Confidential Information. Any documents or presentations distributed to academic supervisors at the University that include Confidential Information will be marked as confidential.

2.4 The Researcher will use the data as "read only", and will not perform updates or corrections to the Confidential Information.

2.5 Nothing contained in this Agreement shall be construed as granting or conferring any rights, either express or implied, under any intellectual property rights, or any rights to use any Confidential Information made available hereunder other than for the limited purposes specified in the Project.

ARTICLE 3: RESTRICTION ON USE OR DISCLOSURE

3.1 The Researcher agrees to use the Confidential Information for research purposes only and agrees not to disclose, sell, license, loan, gift or dispose the Confidential Information in any manner whatsoever, whether digitally, by hard copy, or any other means.

3.2 Copies of the Confidential Information or any subsequent variables or data files derived from the Confidential Information will not be provided to any other individual or organization, except as required by law or court order, in which case the Researcher agrees to give OCE prompt notice of the disclosure order to allow OCE sufficient time to make a reasonable effort to obtain a protective order or other appropriate remedy to prevent such disclosure.

3.3 The Researcher may publish and disclose, without restriction, any research results arising from the performance of the Project, provided that no individual, family, household, business, or organization is identified, with the exception of OCE.

3.4 The Researcher agrees to acknowledge OCE support in any publication or disclosure of research results arising from the performance of the Project.

ARTICLE 4: CONFIDENTIALITY

4.1 Without limitation to the Researcher's obligations under Article 3 above, the Researcher shall maintain all Confidential Information disclosed to it Hereunder in confidence using the same degree of care, safeguard and discretion as it uses with its own similar information that it wishes to hold confidential, but in no event less than a reasonable degree of care and discretion.

ARTICLE 5: SECURITY OF CONFIDENTIAL INFORMATION

5.1 The Researcher shall maintain throughout the Project, administrative, technical, procedural, and physical safeguards sufficient to protect the Confidential Information and to prevent unauthorized access and use.

5.2 The Researcher shall keep an accurate written account of all authorized copies of the Confidential Information, and of work product derived from the Confidential Information, and shall furnish such written logs upon request to OCE.

5.3 In the case where Confidential Information is stored in digital form on a computer, the use of the computer shall be restricted to the Researcher only. In order to use the computer a password must be supplied before access is granted. The password must be a nonsensical combination of numbers and letters. The password must be changed on a regular schedule and never repeated. Storage of the current password must not be in a close proximity to the computer. Any back-up copies of Confidential Information in digital form must be stored in compressed format and password protected.

5.4 In the case where Confidential Information is contained in printed documents, such documents must be kept in a locked drawer or file cabinet when not being referenced by the Researcher. Any printed documents containing Confidential Information that are no longer needed must be shredded before disposal.

5.5 The Researcher agrees to report to OCE any breach of security and any use or disclosure of the Confidential Information not provided for by this agreement, of which it becomes aware within five (5) days of its discovery.

5.6 If, in response to the demand of any individual, OCE requests the Researcher to delete or return that individual's personal information that has been disclosed to Researcher under this Agreement, Researcher will promptly cooperate with OCE to satisfy that request and, where necessary, shall provide OCE with written confirmation once the request has been satisfied.

ARTICLE 6: TERM AND TERMINATION

6.1 This Agreement will remain in effect until the completion of the Project, or 36 months from the Effective Date of this Agreement, whichever comes first. If, at the end of 36 months, access to the Confidential Information is still desired, the Research must request in writing such continued access from OCE.

6.2 The Researcher shall return to OCE each document, including e-mails or other electronic formats, and all other material embodying, containing or based upon Confidential Information and all copies thereof in its possession or control, or shall certify in writing the deletion and destruction of all copies of the Confidential Information, within thirty (30) days of the completion of the Project or expiry of this Agreement.

6.3 Completion of the Project or expiry of this Agreement shall not affect the rights and obligations arising under this Agreement with respect to Confidential Information.

IN WITNESS WHEREOF the parties hereto have executed this Agreement as of the Effective Date.

MARTIN CROTEAU	**ONTARIO CENTRES OF EXCELLENCE INC.**
Signed: ______________	By: ______________
	Name: Dr. Tom Corr
	Title: President and CEO
Date: April 30/12	Date: April 13, 2012

APPENDIX B – CORRELATION MATRIX

	TT	Senior	Title				Prof	Gender		Firm Size				Cash	In-kind	Firm	#Firms	Research	Faculty
	Overall		Staff	Mid	Full	Dist	Rec.	Male	Female	Micro	Small	Medium	Large			Rec.			
TT Overall	1.00																		
Seniority	0.15	1.00																	
Staff	-0.03	-0.11	1.00																
Mid	-0.16	-0.52	-0.14	1.00															
Full	0.16	0.44	-0.17	-0.90	1.00														
Distinguished	0.03	0.36	-0.03	-0.14	-0.17	1.00													
Prof. Track Rec.	0.03	0.09	-0.03	-0.01	0.03	-0.03	1.00												
Male	0.11	0.13	0.05	-0.08	0.04	0.06	0.11	1.00											
Female	-0.11	-0.13	-0.05	0.08	-0.04	-0.06	-0.11	-1.00	1.00										
Micro	0.00	0.04	0.01	0.02	-0.02	-0.02	-0.01	0.01	-0.01	1.00									
Small	-0.03	0.02	-0.08	0.06	-0.02	-0.06	0.13	0.08	-0.08	-0.38	1.00								
Medium	-0.02	-0.04	0.10	-0.09	0.05	0.02	-0.12	-0.06	0.06	-0.36	-0.41	1.00							
Large	0.05	-0.02	-0.04	0.00	-0.01	0.07	0.01	-0.03	0.03	-0.26	-0.30	-0.28	1.00						
Firm Cash	0.10	0.10	-0.04	-0.10	0.08	0.07	-0.08	-0.01	0.01	-0.07	-0.09	0.13	0.03	1.00					
Firm In kind	0.20	0.13	0.01	-0.13	0.12	0.02	-0.01	0.02	-0.02	0.01	0.03	0.00	-0.05	0.46	1.00				
Firm Trk Rec.	0.09	-0.07	0.03	0.03	-0.03	-0.02	-0.02	-0.11	0.11	-0.16	-0.12	0.27	0.01	0.12	-0.02	1.00			
# Firms	-0.03	-0.01	0.00	-0.03	0.04	-0.03	0.02	0.00	0.00	0.03	-0.01	-0.02	0.00	0.29	0.21	-0.06	1.00		
Uni.Research	0.13	0.25	0.09	-0.21	0.16	0.09	0.06	-0.01	0.01	-0.03	-0.05	0.11	-0.05	0.07	0.07	0.11	0.05	1.00	
# Faculty	0.11	0.25	0.05	-0.20	0.16	0.07	0.06	-0.03	0.03	-0.01	-0.04	0.11	-0.07	0.09	0.06	0.09	0.05	0.96	1.00
Operations	-0.09	-0.06	0.08	0.09	-0.11	-0.01	-0.05	0.06	-0.06	-0.01	0.06	-0.07	0.02	0.00	0.06	0.01	0.06	0.01	-0.07
Rep. Rank	-0.10	-0.15	-0.04	0.18	-0.16	-0.01	-0.09	0.05	-0.05	0.01	0.01	-0.12	0.12	-0.07	-0.07	-0.09	0.00	-0.55	-0.57
Awards	0.13	0.18	0.06	-0.21	0.17	0.05	0.00	-0.03	0.03	-0.03	-0.05	0.14	-0.08	0.12	0.12	0.16	0.03	0.74	0.68
Research Rank	-0.11	-0.17	-0.04	0.23	-0.19	-0.09	0.03	0.08	-0.08	-0.01	0.09	-0.17	0.10	-0.09	-0.08	-0.14	0.05	-0.60	-0.57
Inventions	0.10	0.21	0.12	-0.21	0.15	0.06	0.01	-0.04	0.04	0.00	-0.06	0.14	-0.10	0.11	0.07	0.11	0.08	0.84	0.81
TTO Experience	0.16	0.20	0.08	-0.22	0.18	0.03	0.07	-0.03	0.03	-0.04	-0.04	0.12	-0.05	0.10	0.09	0.12	0.04	0.80	0.74
TTO Staff	0.10	0.21	0.08	-0.19	0.15	0.05	0.06	-0.05	0.05	-0.02	-0.01	0.11	-0.09	0.07	0.09	0.11	0.03	0.89	0.87
IP to University	0.04	0.02	0.00	0.07	-0.06	-0.01	0.12	-0.03	0.03	-0.03	0.13	-0.14	0.05	-0.10	0.01	-0.05	0.02	0.14	0.15
IP to Creator	-0.04	-0.02	0.00	-0.07	0.06	0.01	-0.12	0.03	-0.03	0.03	-0.13	0.14	-0.05	0.10	-0.01	0.05	-0.02	-0.14	-0.15
CIT	0.15	0.02	-0.02	-0.04	0.04	0.00	-0.17	-0.03	0.03	-0.06	-0.10	0.17	-0.01	0.15	0.02	0.34	-0.13	0.05	0.03
MM	-0.03	-0.01	-0.11	0.04	0.02	-0.05	0.20	0.03	-0.03	-0.03	0.12	-0.10	0.00	-0.21	-0.02	-0.19	-0.07	0.03	0.02
EET	-0.16	-0.01	0.09	0.00	-0.03	0.03	-0.06	-0.01	0.01	0.07	-0.03	-0.03	-0.01	0.13	0.02	-0.10	0.24	-0.15	-0.12
Photonics	0.10	0.02	0.15	-0.01	-0.07	0.09	-0.05	0.00	0.00	0.05	-0.04	-0.03	0.04	-0.05	-0.01	-0.01	-0.04	0.13	0.13
Earliest	0.21	0.13	0.01	-0.20	0.18	0.04	-0.11	0.09	-0.09	-0.07	-0.11	0.16	0.03	0.34	0.44	0.14	0.08	0.12	0.12
Later	-0.19	-0.13	-0.01	0.17	-0.15	-0.04	0.10	-0.08	0.08	0.11	0.11	-0.15	-0.09	-0.35	-0.42	-0.13	-0.18	-0.12	-0.13
Latest	-0.04	0.00	0.00	0.08	-0.08	0.00	0.02	-0.03	0.03	-0.07	0.01	-0.04	0.11	0.01	-0.05	-0.03	0.19	0.01	0.02
Funding	0.22	0.10	0.00	-0.20	0.20	0.01	-0.13	0.01	-0.01	0.00	-0.11	0.13	-0.03	0.55	0.51	0.14	0.13	0.10	0.10
Length	0.14	0.04	0.00	-0.15	0.15	0.00	-0.17	0.07	-0.07	-0.08	-0.11	0.16	0.04	0.31	0.44	0.06	0.15	0.04	0.06
Distance	-0.06	0.00	0.09	0.05	-0.07	-0.01	0.04	-0.02	0.02	-0.04	0.00	-0.05	0.11	0.02	-0.02	-0.04	0.05	-0.02	-0.02

	Ops	Rep. Rank	Award	Res. Rank	Invent	TTO Exp.	TTO Staff	IP Ownership		Field				Stage			Funding	Length	Dist.
								Uni.	Creator	CIT	MM	EET	Pho.	Earliest	Later	Latest			
Operations	1.00																		
Rep. Rank	0.26	1.00																	
Awards	0.17	-0.63	1.00																
Research Rank	0.13	0.55	-0.83	1.00															
Inventions	0.10	-0.62	0.77	-0.68	1.00														
TTO Experience	-0.06	-0.74	0.88	-0.72	0.85	1.00													
TTO Staff	0.11	-0.77	0.82	-0.69	0.88	0.85	1.00												
IP to University	-0.01	-0.11	0.02	0.22	-0.08	0.17	0.14	1.00											
IP to Creator	0.01	0.11	-0.02	-0.22	0.08	-0.17	-0.14	-1.00	1.00										
CIT	-0.07	-0.11	0.18	-0.20	0.06	0.15	0.06	-0.05	0.05	1.00									
MM	0.06	-0.03	-0.05	0.05	-0.07	-0.04	0.07	0.11	-0.11	-0.57	1.00								
EET	0.02	0.16	-0.17	0.17	-0.03	-0.15	-0.19	-0.13	0.13	-0.25	-0.57	1.00							
Photonics	-0.04	-0.05	0.09	-0.08	0.12	0.11	0.10	0.08	-0.08	-0.10	-0.22	-0.10	1.00						
Earliest	0.02	-0.12	0.22	-0.16	0.13	0.18	0.13	-0.02	0.02	0.32	-0.30	0.09	-0.07	1.00					
Later	0.01	0.10	-0.22	0.17	-0.14	-0.19	-0.12	0.03	-0.03	-0.27	0.26	-0.09	0.08	-0.87	1.00				
Latest	-0.06	0.03	-0.01	0.00	0.00	0.01	-0.02	-0.01	0.01	-0.10	0.08	0.01	-0.01	-0.29	-0.21	1.00			
Funding	-0.04	-0.15	0.21	-0.18	0.12	0.18	0.12	-0.06	0.06	0.46	-0.36	0.01	-0.07	0.63	-0.63	-0.01	1.00		
Length	-0.03	-0.06	0.13	-0.10	0.05	0.09	0.03	-0.06	0.06	0.20	-0.21	0.12	-0.14	0.76	-0.81	0.07	0.63	1.00	
Distance	0.05	0.05	-0.03	0.01	-0.01	-0.04	-0.01	-0.02	0.02	-0.04	-0.03	0.08	-0.03	0.07	-0.07	0.00	-0.02	0.04	1.00

APPENDIX C – REGRESSIONS FOR EMBEDDEDNESS

Univariate Regression Results for Position:

```
Logistic regression                               Number of obs     =        682
                                                  LR chi2(3)        =      17.83
                                                  Prob > chi2       =     0.0005
Log likelihood =  -233.5718                       Pseudo R2         =     0.0368
```

tttotal	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Staff	-.1531224	1.055797	-0.15	0.885	-2.222447	1.916203
Full	1.089278	.2836305	3.84	0.000	.5333723	1.645183
Dist	1.002648	.6717958	1.49	0.136	-.3140472	2.319344
_cons	-2.737249	.2432132	-11.25	0.000	-3.213939	-2.26056

Univariate Regression Results for PhD Age:

```
Multiple-imputation estimates                     Imputations       =         18
Logistic regression                               Number of obs     =        682
                                                  Average RVI       =     0.0480
                                                  Largest FMI       =     0.0835
DF adjustment:   Large sample                     DF:     min       =   2,480.78
                                                          avg       =   3,902.37
                                                          max       =   5,323.96
Model F test:       Equal FMI                     F(   1, 2480.8)   =      12.03
Within VCE type:          OIM                     Prob > F          =     0.0005
```

tttotal	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
profsenior	.0439356	.0126666	3.47	0.001	.0190973	.0687738
_cons	-2.735027	.247753	-11.04	0.000	-3.220725	-2.24933

Bivariate Regression Results for Position and PhD Age:

```
Multiple-imputation estimates                     Imputations       =         18
Logistic regression                               Number of obs     =        682
                                                  Average RVI       =     0.0217
                                                  Largest FMI       =     0.0935
DF adjustment:   Large sample                     DF:     min       =   1,985.10
                                                          avg       = 1320071.12
                                                          max       = 6445551.78
Model F test:       Equal FMI                     F(   4,90068.4)   =       4.82
Within VCE type:          OIM                     Prob > F          =     0.0007
```

tttotal	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Staff	-.1702806	1.05852	-0.16	0.872	-2.244941	1.90438
Full	.8563226	.3100178	2.76	0.006	.2486897	1.463955
Dist	.4193225	.7471616	0.56	0.575	-1.045122	1.883767
profsenior	.0289273	.0151099	1.91	0.056	-.0007056	.0585601
_cons	-3.031856	.2927299	-10.36	0.000	-3.605629	-2.458083

APPENDIX D – DETAILED REGRESSION RESULTS

Logistic regression — Number of obs = 682; LR chi2(25) = 113.62; Prob > chi2 = 0.0000; Pseudo R2 = 0.2343

Log likelihood = -185.67619

tttotal	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Embeddedness						
Staff	-.2055942	1.195657	-0.17	0.863	-2.549039	2.13785
RisingStars	.8150749	.48429	1.68	0.092	-.134116	1.764266
OldSchool	1.108914	.3946707	2.81	0.005	.3353734	1.882454
Laggards	.9164118	.5832512	1.57	0.116	-.2267396	2.059563
Dist	.9424336	.8089285	1.17	0.244	-.6430371	2.527904
firmsize						
Micro	.1291552	.3868262	0.33	0.738	-.6290102	.8873206
Medium	-.2990636	.4094682	-0.73	0.465	-1.101607	.5034794
Large	.3820234	.4102675	0.93	0.352	-.4220861	1.186133
firmrdcash	-.0991951	.2156948	-0.46	0.646	-.5219492	.323559
firmrdkind	.3348773	.1327566	2.52	0.012	.0746791	.5950755
uniresprof	.0038323	.0015801	2.43	0.015	.0007353	.0069293
uniops	-.0001419	.0000969	-1.46	0.143	-.0003319	.0000481
projmonth	.0000596	.0000367	1.62	0.104	-.0000123	.0001315
projfield						
C/IT	1.985012	.5799154	3.42	0.001	.8483982	3.121625
MM	1.714401	.5300465	3.23	0.001	.6755286	2.753273
Photonics	2.799338	.7767681	3.60	0.000	1.276901	4.321776
projstage						
Collab	1.415264	.4006202	3.53	0.000	.6300632	2.200465
PoC	.5662098	.7347713	0.77	0.441	-.8739154	2.006335
ttoinvstaff	.0418637	.0162259	2.58	0.010	.0100615	.0736659
uniip						
Creator	-.2045306	.383388	-0.53	0.594	-.9559572	.546896
profrecord	.0895086	.1157212	0.77	0.439	-.1373007	.3163179
firmrecord	.1111685	.0800312	1.39	0.165	-.0456897	.2680268
profsex						
Female	-1.570569	.7747531	-2.03	0.043	-3.089057	-.0520811
projprox	-.0012937	.0007216	-1.79	0.073	-.002708	.0001206
firmnum	.1375604	.1133574	1.21	0.225	-.0846161	.3597369
_cons	-5.731777	1.355274	-4.23	0.000	-8.388065	-3.075489

```
Conditional fixed-effects logistic regression   Number of obs     =        549
Group variable: uni                             Number of groups  =         10

                                                Obs per group:
                                                              min =          3
                                                              avg =       54.9
                                                              max =        129

                                                LR chi2(21)       =      84.84
Log likelihood  =  -160.6222                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------
     tttotal |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Embeddedness |
      Staff  |  -.2736562   1.187449    -0.23   0.818    -2.601014    2.053701
RisingStars  |   .8643524   .4926111     1.75   0.079    -.1011476    1.829852
  OldSchool  |   1.141634   .3966635     2.88   0.004     .3641879     1.91908
   Laggards  |   .9454032   .5995108     1.58   0.115    -.2296163    2.120423
       Dist  |   .7814261   .8211182     0.95   0.341     -.827936    2.390788
             |
    firmsize |
      Micro  |   .1653181   .3892685     0.42   0.671    -.5976341    .9282703
     Medium  |  -.2882426    .417884    -0.69   0.490     -1.10728     .530795
      Large  |    .382423   .4200148     0.91   0.363    -.4407909    1.205637
             |
  firmrdcash |  -.0993083   .2186366    -0.45   0.650    -.5278282    .3292115
  firmrdkind |   .3684379   .1393065     2.64   0.008     .0954022    .6414737
   projmonth |   .0000539   .0000367     1.47   0.142     -.000018    .0001259
             |
   projfield |
       C/IT  |   2.573035   .7015371     3.67   0.000     1.198047    3.948022
         MM  |   2.371468   .6706263     3.54   0.000     1.057065    3.685871
  Photonics  |   3.483574   .8595752     4.05   0.000     1.798837     5.16831
             |
   projstage |
     Collab  |   1.427591   .4132929     3.45   0.001     .6175516     2.23763
        PoC  |    .589117   .7440166     0.79   0.428    -.8691288    2.047363
             |
  profrecord |   .0616638   .1150289     0.54   0.592    -.1637887    .2871163
  firmrecord |   .1299074   .0846772     1.53   0.125    -.0360569    .2958717
             |
     profsex |
     Female  |  -1.471948   .7862234    -1.87   0.061    -3.012918    .0690216
    projprox |  -.0012383   .0007495    -1.65   0.098    -.0027073    .0002306
     firmnum |   .1241633   .1126231     1.10   0.270    -.0965739    .3449005
------------------------------------------------------------------------------
```

```
Multinomial logistic regression                   Number of obs     =        663
                                                  LR chi2(46)       =     141.25
                                                  Prob > chi2       =     0.0000
Log likelihood = -220.86339                       Pseudo R2         =     0.2423

------------------------------------------------------------------------------
      tttype |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Failure      |  (base outcome)
-------------+----------------------------------------------------------------
License      |
Embeddedness |
RisingStars  |   .8502728   .6781791     1.25   0.210    -.4789338     2.17948
  OldSchool  |   1.521819   .5312949     2.86   0.004     .4804999    2.563138
   Laggards  |   -.133809   .9831059    -0.14   0.892    -2.060661    1.793043
       Dist  |   1.589266   1.034296     1.54   0.124    -.4379171    3.616449
             |
    firmsize |
      Micro  |   .3422284   .5227886     0.65   0.513    -.6824184    1.366875
     Medium  |  -.0174598   .5516767    -0.03   0.975    -1.098726    1.063807
      Large  |   .0473857   .5854471     0.08   0.935     -1.10007    1.194841
             |
  firmrdcash |  -.0383469   .1716312    -0.22   0.823    -.3747379    .2980442
  firmrdkind |   .4950969   .1476998     3.35   0.001     .2056106    .7845831
  uniresprof |    .002873   .0023023     1.25   0.212    -.0016394    .0073854
      uniops |   1.66e-06   .0001309     0.01   0.990    -.0002549    .0002582
   projmonth |   .0000482   .0000474     1.02   0.310    -.0000448    .0001412
             |
   projfield |
       C/IT  |     2.2867   .7267186     3.15   0.002     .8623578    3.711042
         MM  |   1.581414     .66552     2.38   0.017     .2770185    2.885809
  Photonics  |   3.634058   .9656679     3.76   0.000     1.741384    5.526732
             |
   projstage |
     Collab  |   2.345605   .7261048     3.23   0.001     .9224661    3.768745
        PoC  |   2.068736   1.058952     1.95   0.051     -.006771    4.144243
             |
 ttoinvstaff |   .0710827   .0231367     3.07   0.002     .0257356    .1164298
             |
       uniip |
    Creator  |   -.840777   .5183284    -1.62   0.105    -1.856682    .1751279
  profrecord |  -.1464046   .2209565    -0.66   0.508    -.5794713    .2866621
  firmrecord |   .0548849   .1117498     0.49   0.623    -.1641406    .2739104
    projprox |  -.0015852    .000893    -1.78   0.076    -.0033354     .000165
     firmnum |   .2559855   .1216372     2.10   0.035      .017581      .49439
       _cons |  -9.004925   2.007885    -4.48   0.000    -12.94031   -5.069544
-------------+----------------------------------------------------------------
Startup      |
Embeddedness |
RisingStars  |   .9998059   .6619988     1.51   0.131    -.2976878      2.2973
  OldSchool  |   1.153779   .5575492     2.07   0.039     .0610025    2.246555
   Laggards  |   1.558723   .7277465     2.14   0.032     .1323659     2.98508
       Dist  |   .7280654   1.225037     0.59   0.552    -1.672964    3.129094
             |
    firmsize |
      Micro  |  -.1991606   .5297973    -0.38   0.707    -1.237544     .839223
     Medium  |  -.5014456   .5904473    -0.85   0.396    -1.658701    .6558098
      Large  |   .7650961   .5369483     1.42   0.154    -.2873033    1.817495
             |
  firmrdcash |  -.9473237   .6185977    -1.53   0.126    -2.159753    .2651055
  firmrdkind |  -.0835775   .2679565    -0.31   0.755    -.6087625    .4416076
  uniresprof |   .0053512    .002142     2.50   0.012     .0011529    .0095495
      uniops |   -.000301   .0001504    -2.00   0.045    -.0005957   -6.19e-06
   projmonth |   .0000906   .0000487     1.86   0.063    -4.86e-06    .0001861
             |
   projfield |
       C/IT  |   1.848731   1.132623     1.63   0.103    -.3711696    4.068631
         MM  |   2.464374   1.060557     2.32   0.020     .3857216    4.543027
  Photonics  |   3.096779   1.342515     2.31   0.021     .4654981     5.72806
             |
   projstage |
     Collab  |   1.122538   .4972998     2.26   0.024     .1478479    2.097227
        PoC  |  -.7921927   1.170153    -0.68   0.498     -3.08565    1.501264
             |
 ttoinvstaff |    .021927   .0226052     0.97   0.332    -.0223784    .0662324
             |
       uniip |
    Creator  |   .5693998   .5703937     1.00   0.318    -.5485514    1.687351
  profrecord |    .257173   .1351743     1.90   0.057    -.0077637    .5221096
  firmrecord |   .1016551   .1145379     0.89   0.375    -.1228351    .3261453
    projprox |  -.0005878   .0009737    -0.60   0.546    -.0024961    .0013205
     firmnum |  -.3398707    .337007    -1.01   0.313    -1.000392    .3206509
       _cons |  -4.986847   2.083256    -2.39   0.017    -9.069954   -.9037395
------------------------------------------------------------------------------
```

APPENDIX E – GOODNESS-OF-FIT TESTS

Binomial Logit Models:

	Final Model	Version 3 Model	Version 2 Model
N:	682	682	682
Log-Lik Intercept Only:	-242.488	-242.488	-242.488
Log-Lik Full Model:	-191.814	-188.92	-185.676
D:	383.627(662)	377.839(660)	371.352(650)
LR:	101.349(15)	107.137(17)	113.624(25)
Prob > LR:	0	0	0
McFadden's R2:	0.209	0.221	0.234
McFadden's Adj R2:	0.126	0.13	0.102
Maximum Likelihood R2:	0.138	0.145	0.153
Cragg & Uhler's R2:	0.271	0.286	0.302
McKelvey and Zavoina's R2:	0.407	0.474	0.511
Efron's R2:	0.175	0.179	0.197
Variance of y*:	5.549	6.252	6.73
Variance of error:	3.29	3.29	3.29
Count R2:	0.894	0.899	0.899
Adj Count R2:	0.077	0.115	0.115
AIC:	0.621	0.619	0.638
AIC*n:	423.627	421.839	435.352
BIC:	-3935.942	-3928.68	-3869.917
BIC':	-3.473	3.789	49.502

Multinomial Logit Models:

	Final Model	Version 2 Model	Difference
N:	663	663	0
Log-Lik Intercept Only:	-291.489	-291.489	0
Log-Lik Full Model:	-225.065	-220.863	-4.202
D:	450.131(594)	441.727(576)	8.404(18)
LR:	132.848(36)	141.252(46)	-8.404(-10)
Prob > LR:	0	0	0
McFadden's R2:	0.228	0.242	-0.014
McFadden's Adj R2:	-0.009	-0.056	0.047
Maximum Likelihood R2:	0.182	0.192	-0.01
Cragg & Uhler's R2:	0.31	0.328	-0.018
Count R2:	0.887	0.885	0.002
Adj Count R2:	0.026	0.013	0.013
AIC:	0.887	0.929	-0.042
AIC*n:	588.131	615.727	-27.596
BIC:	-3408.954	-3300.416	-108.538
BIC':	101.036	157.6	-56.564

APPENDIX F – BNL WITH UPDATED RESEARCH FIELD

```
Logistic regression                             Number of obs     =        682
                                                LR chi2(14)       =      99.56
                                                Prob > chi2       =     0.0000
Log likelihood = -192.70812                     Pseudo R2         =     0.2053

------------------------------------------------------------------------------
     tttotal |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Embeddedness |
      Staff  |  -.2023453   1.123283    -0.18   0.857    -2.403939    1.999248
RisingStars  |   .7690111   .4640622     1.66   0.097    -.1405341    1.678556
  OldSchool  |   1.114687   .3788543     2.94   0.003     .3721457    1.857227
   Laggards  |   .9942004   .5560402     1.79   0.074    -.0956184    2.084019
       Dist  |    .844972   .7527179     1.12   0.262    -.6303281    2.320272
             |
  firmrdkind |   .3230572   .1259238     2.57   0.010     .0762511    .5698633
  uniresprof |   .0041535   .0014466     2.87   0.004     .0013182    .0069889
   projmonth |   .0000626    .000034     1.84   0.066    -4.08e-06    .0001292
             |
  projfield2 |
        CIT  |   2.117435   .5279502     4.01   0.000     1.082671    3.152198
         MM  |   1.723408   .5149504     3.35   0.001     .7141234    2.732692
             |
   projstage |
   Earliest  |   1.272518   .3822896     3.33   0.001     .5232439    2.021792
     Latest  |   .6479733   .7041868     0.92   0.357    -.7322074    2.028154
             |
 ttoinvstaff |   .0444072   .0151621     2.93   0.003     .0146901    .0741244
             |
     profsex |
     Female  |   -1.51839   .7609411    -2.00   0.046    -3.009807   -.0269726
       _cons |  -7.265715   .8283981    -8.77   0.000    -8.889346   -5.642085
------------------------------------------------------------------------------
```