FACTORS AFFECTING THE QUALITY OF JOINT PATENTS IN CHINA

RUOYING ZHOU

Doctor of Philosophy

ASTON UNIVERSITY

September 2017

Dedication

This thesis is dedicated to Yanchun, Shouxing, Wenli, Chongfa, and Shiyang.

Acknowledgement

There have been many people who have walked alongside me during the past four years.

I would like to express my deepest gratitude to my supervisors Mr Kirit Vaidya and Dr Michail Karoglou, for their unwavering support, collegiality, and mentorship throughout the PhD journey. Without them completing the PhD would have been so much more difficult.

I would like to extend my thanks to those who offered collegial guidance over the years: Dr Yundan Gong and Professor Jun Du.

My gratitude also goes to Ms Ranjit Judge and Ms Jeanette Ikuomola for providing a friendly working environment.

Aston University

Factors Affecting the Quality of Joint Patents in China

Ruoying Zhou

Doctor of Philosophy

2017

Thesis Summary

This thesis expects to contribute to the understanding of the factors affecting the quality of joint patents based on empirical investigations using large datasets.

The first empirical study looks at the propensity of different technology level sectors to engage in joint patenting activities. Higher industrial sectors are more likely to collaborate with universities for technological innovations.

The second empirical study analyses the effects of co-ownerships with cross-border partners and universities on the quality of joint patents owned by Chinese firms. While cross-border co-ownership on its own is a strong predictor of joint patent quality, the positive effect of university co-ownership on quality is clearly observed when cross-border co-ownership is added. The evidence on the effect of organisational proximity (joint patents between subsidiaries of an enterprise) is ambiguous.

The third empirical study investigates whether the relationships observed in China are also found in international evidence by using a larger data set for 80 countries covering industrialised emerging and developing countries. Collaborations between countries with substantial income differences, for example emerging and developed countries, positively impact on joint patent quality. Collaborations between low-income countries have been unsuccessful in improving patent quality.

The fourth empirical study explores the roles of cognitive proximity and organizational proximity in shaping the innovation performance of firm-university collaborations in China. Cognitive proximity has a positive impact on the quality of joint patents. However, beyond a certain level of cognitive proximity, the positive impact on value creation diminishes. Organizational proximity is insignificantly related to the value of joint patents.

In summary, joint patenting performance is stronger where there is greater cognitive proximity of firms with cross-border partners and universities and firms have a sufficiently high level of technological capacity. Generally organizational proximity is less significant.

Key words: research and development, patenting, collaboration, forward citation, technology

List of Contents

List of Abbreviations....9
List of Tables....10
List of Figures....11
Chapter 1 Introduction....12
1.1 Background of Research....12
1.2 Context of Research....15
1.3 Motivation and Research Objectives....21
1.4 Structure of the Thesis....27
Chapter 2 A Review of the Literature....29
2.1 Introduction to the Literature Review....29
2.2 Why Collaborate for Innovation....29
2.2.1 Brief overview of collaboration....30
2.2.2 Motives for engaging in R&D collaboration....32
2.2.3 Theories of relevance....35
2.3 Who Collaborate for Innovation....36
2.3.1 The importance of collaboration across boundaries....37
2.3.2 Collaboration between key innovators and innovation performance....39
2.4 How to Measure Performance of R&D Collaboration....40
2.4.1 Forward citations....42
2.5 Overview....43
Chapter 3 Data Source....45
3.1 Purpose of the Chapter....45
3.2 PATSTAT Explained....45
3.3 Setup of datasets....47
3.4 Variables....51
3.4.1 Number of technology fields....54
3.4.2 Number of inventors....54
3.4.3 Number of forward citations....54
3.4.4 Number of backward citations....55
3.4.5 Number of NPL citations....55
3.4.6 Technology field dummies.....56
3.4.7 Patent claims....56

3.4.8 Patent family size 57
3.5 Econometric methods 58
Chapter 4 The Propensity of Technological Collaborations 60
4.1 Introduction 60
4.2 Literature Review and Hypotheses Development 61
4.3 Econometric Analysis 63
4.3.1 Source of Data 63
4.3.2 Measures 64
4.3.4 Econometric model 65
4.4 Results 67
4.5 Chapter summary 73
Chapter 5 Co-ownership and Joint Patent Quality 75
5.1 Introduction 75
5.2 Literature Review 77
5.2.1 Cross-border co-ownership 79
5.2.2 University co-ownership 79
5.2.3 The Presence of Organisational Proximity 81
5.3 Data 82
5.3.1 Source of Data 82
5.3.2 Measures 84
5.4 Results 88
5.4.1 Benchmark results 89
5.4.2 Main results and discussion 93
5.4.3 Robustness test 98
5.5 Chapter summary 100
Chapter 6 The Effects of Co-ownerships on Joint Patent Quality Re-examined – Evidence from 80 countries 103
6.1 Introduction 103
6.2 Literature review 105
6.2.1 International technological collaboration as a source of innovation 105
6.2.2 University collaboration as a source of innovation 106
6.3 Data 108
6.3.1 Source of Data 108
6.3.2 Measures 113
6.3.3 Econometric analysis 115

6.4 Results...115
6.4.2 Main results and discussion...120
6.4.2 Robustness test...124
6.5 Chapter summary...125
Chapter 7 Proximity in Industry-University Collaborations...128
7.1 Introduction...128
7.2 Industry-University Relations in China...130
7.2.1 Industry-University Interactions in the Planned Era (1953-1978)...130
7.2.2 Industry-University Interactions in the post-reformation era (1978-present)...130
7.2.3 The Establishment of University Enterprises...131
7.3. Proximity in Industry-University Collaboration in China...133
7.3.1 Cognitive Proximity...134
7.3.2 Organisational Proximity...135
7.4 Data...137
7.4.1 Source of data...137
7.4.2 Measures...138
7.4.3 Econometric analysis...142
7.5 Results...143
7.5.1 Benchmark results...143
7.5.2 Main results and discussion...146
7.5.3 Robustness test...150
7.6 Chapter summary...152
Chapter 8 Conclusion...154
List of References...159
Appendix 1 Test for multicollinearity among variables (Chapter 5)...176
Appendix 2 Model effects of OLS (Chapter 5)...177
Appendix 3 Model effects of PQMLE (Chapter 5)...179
Appendix 4 Marginal effects of PQGPMLE (Chapter 5)...181
Appendix 5 Further analysis of cross-border collaboration...183
Appendix 6 Model effects of PQGPMLE (Chapter 5)...184
Appendix 7 Model effects of NB1 (Chapter 5)...187
Appendix 8 Model effects NB2 (Chapter 5)...189
Appendix 9 List of countries in sample (Chapter 5)...191
Appendix 10 Model effects of OLS (Chapter 5)...192

Appendix 11 Model effects of PQMLE (Chapter 5) 194
Appendix 12 Marginal effects of PQMLE (Chapter 5) 196
Appendix 13 Model effects of PQGPMLE (Chapter 5) 198
Appendix 14 Model effects of NB1 (Chapter 5) 200
Appendix 15 Model effects of NB2 (Chapter 5) 202
Appendix 16 Model effects of OLS (Chapter 6) 204
Appendix 17 Model and marginal effects of PQMLE (Chapter 6) 205
Appendix 18 Aggregations of manufacturing based on NACE Rev 1.1 207

List of Abbreviations

AME	Average Marginal Effect
BIC	Brazil, India, and China
EU	European Union
EPO	European Patent Office
GDP	Gross Domestic Product
GLM	Generalized Linear Model
H-H	High income country – High income country
HT	High Technology
IP	Intellectual Property
IPC	International Patent Classification
LT	Low technology
L-L	Low-income country - Low income country
L-LM	Low-income country – Lower-middle income country
L-UM	Low-income country – Upper-middle income country
LM-LM	Lower-middle income country – Lower-middle income country
LM-UM	Lower-middle income country – Upper-middle income country
L-H	Low income country – High income country
LM-H	Lower-middle income country – High income country
MHT	Medium-high technology
MLT	Medium-low technology
MNE	Multinational enterprise
NB	Negative binomial
NB1	Negative binomial regression model with linear variance function
NB2	Negative binomial regression model with quadratic variance function
NIS	National Innovation System
NPL	Non-patent literature
OLS	Ordinary Least Square
PATSTAT	Patent Statistical Database
POE	Privately-owned enterprise
PRI	Public research institute
PQMLE	Poisson quasi-maximum likelihood estimator with robust standard errors
PQGPMLE	Poisson quasi-generalized pseudo-maximum likelihood estimator with robust standard errors
RBV	Resource-based view
R&D	Research and Development
SIPO	State Intellectual Property Office
S&T	Science and Technology
SOE	State-owned enterprise
UK	United Kingdom
USA	United States of America
USPTO	United States Patent and Trademark Office
UM-H	Upper-middle income country – High income country
VIF	Variance inflation factor
WIPO	World Intellectual Property Organization

List of Tables

Table 1. 1 Research objectives for the main chapters. 25

Table 3. 1 Number of firms and joint patents by year..48
Table 3. 2 Top 10 applicants in the sample. 50
Table 3. 3 Variables and definitions...52

Table 4. 1 Summary statistics for variables 68
Table 4. 2 Spearman's correlation matrix for variables 69
Table 4. 3 Probit regression results 70

Table 5. 1 Definition of variables and summary statistics 84
Table 5. 2 Correlation matrix for all variables..87
Table 5. 3 Benchmark results of PQGPMLE...90
Table 5. 4 Main results of NB1 94
Table 5. 5 Robustness test by NB2 99

Table 6. 1 Summary statistics 117
Table 6. 2 Benchmark results of PQGPMLE...118
Table 6. 3 Main results of NB1 120
Table 6. 4 Robustness test by NB2 124

Table 7. 1 Descriptive statistics 139
Table 7. 2 Pearson's correlation matrix 140
Table 7. 3 Benchmark model effects and marginal effects of PQGPMLE 144
Table 7. 4 Main model effects and marginal effects for of NB1...147
Table 7. 5 Robustness model effects and marginal effects of NB2 151

List of Figures

Figure 1. 1 Trends in joint patenting activities: 1985-2010 18
Figure 1. 2 Trends in joint patenting between firm and university, and between firm and PRI: 1985-2010 20

Figure 5. 1 Trends in joint patenting and co-ownerships 83

Figure 6. 1 Trends in joint patenting with universities 110
Figure 6. 2 Trends in joint patenting with cross-border partners 111
Figure 6. 3 Trends in cross-border joint patenting based on World Bank's country classifications 112

Chapter 1 Introduction

1.1 Background of Research

This thesis is a collection of empirical chapters on joint patenting, which is a phenomenon that a patent is claimed ownership by more than one organisation. Joint patent may combine information on R&D collaboration and Intellectual Property (IP) sharing arrangement (Belderbos et al., 2014). According to the literature, the following circumstances are likely to result in joint patenting: 1) when the scale of the R&D project is small, it is difficult to divide the intellectual property among the partners (Hagedoorn, 2003); 2) when patentable outputs have the potential to become a core advantage for one partner and subsequently a dispute among partners (Teng, 2007); 3) participating firms engaged in joint patenting activities in the past (Hagedoorn et al., 2003). In summary, joint patenting is an important form of R&D collaboration and it tends to occur in high-tech industries and emerging technical areas.

In the literature, joint patenting is explored under various other names: patent collaboration, technological collaboration, co-patenting, and R&D collaboration. Joint patenting is discussed in the literature of two main subject areas: international business, and innovation. The phenomenon is firstly documented in the international business literature.

Guellec and Van Pottelsberghe de la Potterie (2001) analyse the internationalisation of technological activities of multinational firms in the Organisation for Economic Co-operation and Development (OECD) area, and find that countries are more likely to collaborate if they are geographically close to each other, if they share a common language, and if they have a similar technological specialisation.

Studying collaborations among inventors in 109 European regions, Maggioni et al. (2007) illustrate that business and public R&D expenditure and the similarity of innovative structure of the regions are significant variables that explain the structure of co-patents.

Using innovative measures of R&D internationalisation, Picci (2010) shows that the amount of bilateral patent collaboration is positively affected by the presence of a common language, a common border and by more similar cultural characteristics.

Using a novel database on companies' country or origin, Montobbio and Sterzi (2013) confirm that technological proximity and sharing a common language are key drivers of international technological collaborations, as measured by co-patents between two countries.

Studying countries collaborating with China in technological production, Chen et al. (2013) show that relative manufacturing strength, international trade exposure, and the respective economy standing are positively associated with the propensity for engaging in international co-invention activities. All above reviewed studies adopt a country approach to look at joint patenting. The main disadvantage with country-level studies is that their findings cannot be used to understand behaviour of smaller users, such as sectors and firms. This aggregated approach fails to take account the heterogeneity existing in sectors and firms. We need to rely on a smaller unit analysis.

In the innovation literature, a few papers specifically explore joint patenting are mainly focused on developed countries. The earliest research on joint patenting is Hagedoorn's (2003). Hagedoorn (2003) firstly analyses the motivations of firms to enter into joint patenting agreements. He argues that the strength or weakness of a regime of appropriability could affect the degree to which certain industries have a higher or lower propensity to establish joint patents.

Later research tends to provide a patent-level analysis on the topic. Briggs (2014) empirically shows that inventions that are collaboratively patented are higher quality than those patented by a single firm.

Belderbos et al. (2014) explore the effect of R&D collaboration resulting in the co-ownership of a patent at both patent and firm levels, using single patenting as reference group. Their findings illustrate that while interindustry co-patenting is positively associated with patent quality, university co-patenting is positively linked to firm's market value.

Briggs (2015) investigates the effect of multi-country and university co-ownerships on patent quality and finds that multi-country co-ownership in countries with similar income levels enhances the likelihood a joint patent is high quality in the short run, whereas university co-ownership is found to have a positive impact on the patent quality in the long run. A common issue of all reviewed innovation literature is that they focus on developed countries - we know little about joint patenting in emerging and developing countries. To the best of my knowledge, this thesis is the first contribution to assess the trends, motivation, and performance of joint patenting in a major emerging country – China.

Technological knowledge is a prerequisite for innovation breakthrough. Due to time constraints (Tsai and Wang, 2009), high costs and risks (Das and Teng, 2000) associated with creating and developing technologies, access to technological knowledge outside firm's boundary has increasingly become an alternative to in-house R&D. A firm can access to such knowledge through collaborating with different partners, including suppliers, customers, competitors, universities, and foreign institutions.

The empirical investigation of the thesis begins by studying the relationship between the level of technology sectors and the propensity to engage in joint patenting activities. The results find that higher industrial sectors are more likely to collaborate with universities for technological innovations. Absorptive capacity (Cohen and Levinthal, 2000) plays a key role in determining the degree of innovativeness of joint patents.

The relationship between these collaborators and innovation performance is an important topic in the innovation literature. This thesis joins the debate regarding whether university and foreign collaborations are positively related to innovation performance. Based on empirical investigations using large data sets of China, the findings of the thesis's empirical studies show that cross-border partners and universities are strong predictors of patent quality.

Then, the empirical chapter looks at whether the relationships observed in China are also found in international evidence by using a larger data set for 80 countries covering industrialised emerging and developing countries. The findings reveal that collaborations between countries with substantial income differences positively impact on joint patent quality. Collaborations between low-income countries have been unsuccessful in improving patent quality.

Lastly, the empirical investigation explores the relationship between proximity and innovation performance. The evidence shows that cognitive proximity has a positive impact on the quality of joint patents. However, beyond a certain level of cognitive proximity, the positive impact on value creation diminishes.

1.2 Context of Research

The context of research is China, which is an interesting case. Starting as a developing country with only a few patent applications in the 1980s, China has now shown the highest growth in patent applications, ranked sixth out of the top ten countries of origin (China Daily, 2017). The patent boom suggests substantial improvement in technological capabilities of domestic firms. It is a stark contrast to its humble past, when the technological capabilities of domestic firms were weak and science and technology (S&T) activities were stagnant.

There were two outstanding structural deficiencies (Eun et al., 2006). The first structural deficiency was the separation of research function from production processes. Based on the Soviet Model, public research institutes (PRIs) conducted research projects guided by the five-year national plans and other plans, and produced the prototype that State-owned enterprises (SOEs) could reproduce on a larger scale. SOEs were ordered to focus on production only. It was ministries in charge of the SOEs that made strategic decisions on SOEs' internal businesses such as company strategy, R&D, and marketing activities.

The second structural deficiency was concerned with the prominent role played by public research institutes, and to a lesser extent, by universities in China's innovation system (Boeing et al., 2016). PRIs and universities undertook more than two-thirds of the nation's R&D projects, whereas less than one-third of those were conducted by SOEs. The private firms were not allowed to enter certain industries and were facing difficulties of access to credit, therefore these firms hardly benefited from the R&D findings of research organisations.

Formal collaboration between industry and academia was so rare that the latter could not provide scientific support for backing commercialization with scientific discoveries. For a long time, the desire of industry to collaborate with universities on innovations remain low, partly due to the negligence of the total innovation capacity concept, which supports greater collaboration among major innovators of the NIS, i.e. government research institutes, universities, and firms (Guan et al., 2005).

In a stark contrast, numerous initiatives have been launched throughout the industrialized countries since the 1970s. For instance, in the United States, the Bayh-Dole Act has been praised by many scholars for its role in facilitating university-industry technology transfer. The Act permits universities and other non-governmental organisations to pursue ownership of inventions arising from federal government-funded research. After the Act, there has been a surge in the United States (US) universities' involvement in patenting and licensing, and in establishing technology transfer offices. The Act was a part of U.S. policy to strengthen protection for intellectual property rights (Mowery, 2005).

To resolve these barriers for S&T advancement referred to above, the Chinese government carried out a series of significant structural reforms since 1978 (marked by five significant national S&T conferences, held in 1978, 1985, 1995, 1999 and 2006). The issue of 'the Resolution of the Central Committee of the Communist Party of China' on the structural reform of the S&T system' made it clear that 'economic development must rely on S&T, while S&T research must render services to economic construction'. The state policies arise from the reforms focused on reforming the funding system, developing high-tech industries, encouraging private R&D-intensive enterprises, and promoting industry-academia linkages. In the early 2000s, R&D collaborations between firms, and between firms and universities began to increase, as observable by joint patent applications (Figure 1.1).

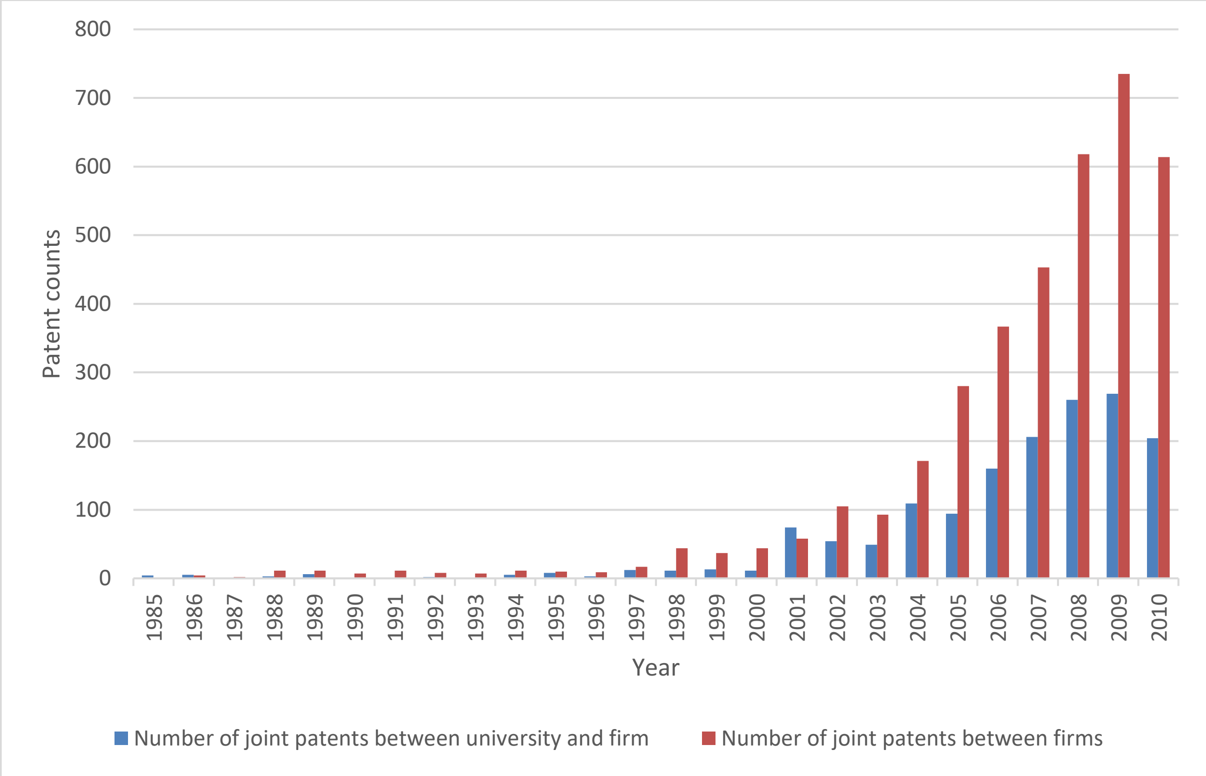

Figure 1. 1 Trends in joint patenting activities: 1985-2010

(Source: author's own calculation based on joint patent data from the European Patent Office)

Schaaper (2009) suggests that joint patenting is a key area where knowledge sharing activities among key innovation performers were channelled in China. Statistics show that the joint patenting pattern in the country has been subjected to major changes since 2000, due to the S&T reform that downsized a large number of government research institutes and S&T personnel. The consequences are measurable (see Figure 1.2): while the number of joint patents owned by government research institutes and industrial enterprises dropped significantly, the number of joint patents filed by universities and industrial enterprises rise substantially. Evidence of joint patents clearly reflects the shift of focus of governmental policy, which leads to an important change within China's innovation system: universities start making their presence in the nation's S&T and economic development. Clearly, joint patenting is an important window for examining the development and transformations within China's innovation system. Studying joint patenting not only helps unfold the trends and patterns of R&D collaborations in the country, but also helps improve current understanding on the performance of these collaborations. Better insights into collaboration strategies and their impact on innovation performance would allow the formulation of an open technology policy.

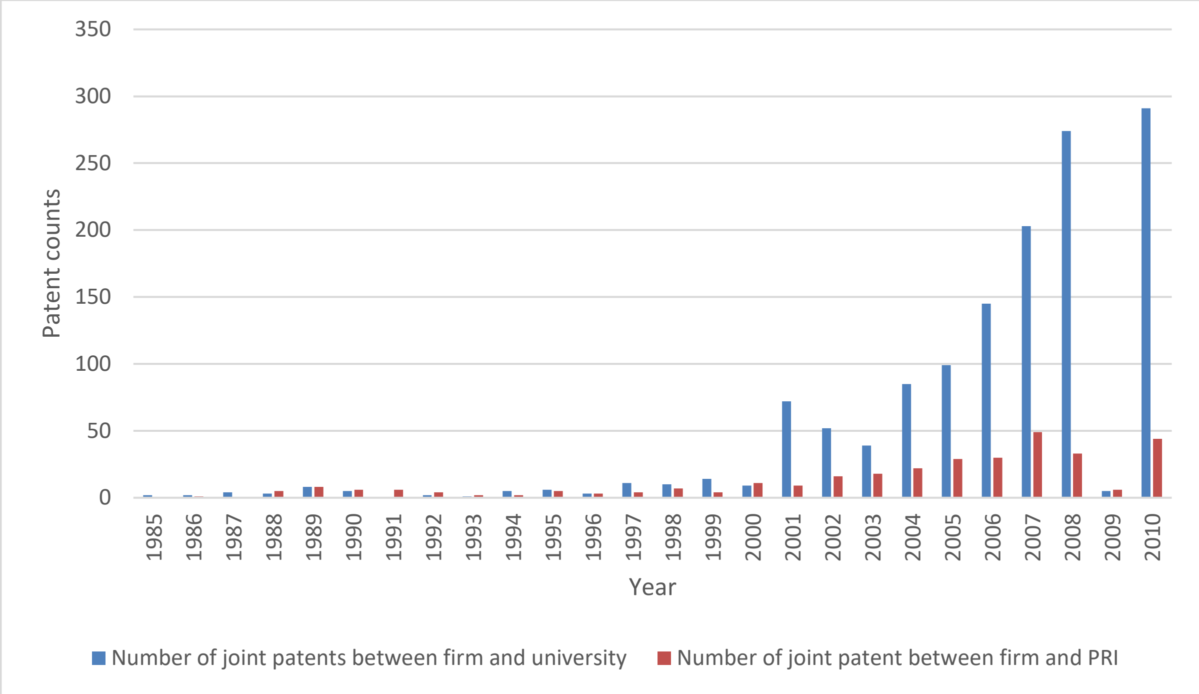

Figure 1. 2 Trends in joint patenting between firm and university, and between firm and PRI: 1985-2010

(Source: author's own calculation based on joint patent data from the European Patent Office)

1.3 Motivation and Research Objectives

Given the importance of R&D interaction in generating innovations, as well as the growing importance of joint patenting in innovation activities, this thesis empirically explores impact of joint patenting on innovation performance of firms (using patent indicators). The motivation and research objectives for each empirical chapter are discussed as follows.

The importance of high-technology in national economic growth has been well-documented (Schartinger et al., 2002). In many countries, universities participate in important R&D projects of the states. Likewise, high-technology has been the driving force of economic growth by Chinese government and university an important source of cutting-edge technologies for domestic firms.

To the best of my knowledge, studies related to collaborations between university and different technological sectors are mostly conducted in the Western economies; the same phenomenon in emerging countries is insufficiently investigated. As an emerging economy and going through rapid industrial and technological change, China has attracted lots of discussion from the academia on important policy changes, such as those guide the S&T reforms. Due to differences in the path of economic development and other reasons, it is likely to obtain a different picture of collaborations between universities and firms of different technological level.

The research objective of first empirical chapter (Chapter 4) is to explore the relationship between the level of technology sector and the propensity to enter research partnership with universities. The empirical findings show that firms in high-technology sectors are more likely to collaborate with universities.

Since joint patenting is important evidence of collaborative R&D, getting a good understanding of firms' collaboration strategies not only helps form right strategy of developing R&D, but also provides implications for policy makers to better shape future technology policies. Among many collaboration strategies, university, international, and internal collaboration (i.e.

organisational proximity) are popular choices for firms. Given that joint patenting is better than sole patenting in terms of generating valuable inventions, the research objective of the second empirical chapter (Chapter 5) is to analyse and compare the effects of university and cross-border, as well as organisational proximity on joint patent quality, which is measured by the number of forward citations received within five years. The empirical findings confirm the positive effects of university and cross-border co-ownerships on joint patent quality.

The previous chapter confirms that cross-border collaboration plays a positive role in enhancing the quality of joint patents of Chinese firms. For developing countries, cross-border R&D collaboration is a major channel of absorbing knowledge from developed countries, which is key driver of catching up and income growth (Fagerberg, 1994; Grossman and Helpman, 1991). Such collaboration provides a platform for firms to expand their knowledge base and subsequently sustain competitiveness (Briggs, 2015). Drawing upon a larger sample covering joint patent observations for 80 countries, the first objective of the third empirical chapter (Chapter 6) is explore the effect of cross-border co-ownership on joint patent quality.

Cross-border collaboration is divided into eight types based on World Bank's country classifications. The World Bank assigns a country to one of the following categories: (1) low-income country; (2) lower-middle income country; (3) upper-middle income country; (4) high-income country.

The eight types of cross-border collaboration are formed based on different combinations of the World' Bank's country classifications: 1) collaboration between low income countries, between low and lower middle income countries, and between low and upper middle income countries; 2) collaboration between lower middle countries; 3) collaboration between lower middle and upper middle income countries; 4) collaboration between upper middle income countries; 5) collaboration between low and high income countries; 6) collaboration lower middle and high income countries; 7) collaboration between upper middle and high income countries; 8) collaboration between high income countries. My empirical finding illustrates that cross-border co-ownership is a strong indicator for joint patent quality.

University collaboration is another popular collaboration strategy used by firms. Compared with industrial firms, universities differ in cognitive attitudes and operational practices (Bonaccorsi and Thoma, 2007). The second research objective of this chapter is to investigate the effect of university co-ownership on joint patent quality. Compared with the previous chapter, this chapter further divides university collaboration into domestic and international collaboration based on geographical proximity [1]. Empirical finding shows that domestic university collaboration is conductive to high quality patent.

Although universities are potentially valuable collaboration partners for developing innovations, not all the firms find it easy to establish a link with universities and capture values from R&D collaboration due to various reasons. There has been an on-going interest in the management and economic literature to study factors that affect the success of R&D collaboration with universities (e.g. Fontana et al., 2006; Maietta, 2015). One established finding from these researches is that absorptive capacity of a firm determines how much it can appropriate from R&D collaboration (Cohen and Levinthal, 1989).

Proximity (i.e. similarities) between partners – a newer area of research, has been receiving growing attention from the literature. Yet, empirical findings on the role of proximity in shaping the outcome of university-industry interaction are mixed. The number of relevant literature for China is relatively small.

To fill the gap in the literature, I intend to explore the relationship between proximity dimensions and joint patent quality (using forward citations) in the fourth empirical chapter (Chapter 7), which has two research objectives. The first objective is to explore whether sharing similar

[1] In this chapter, university collaboration is divided into domestic university collaboration and international university collaboration

knowledge bases (cognitive proximity) is conductive to high quality patent. The second objective is to investigate whether collaboration (organizational proximity) between different units of the same organization is conductive to high quality patent. The empirical findings confirm the inverted U-shaped effect of cognitive proximity on joint patent quality.

Table 1.1 lists research objective(s) for each empirical chapter.

Table 1. 1 Research objectives for the main chapters.

Empirical chapter	**Research objective(s)**
Chapter 4	(1) To explore the relationship between the level of technology sector and the propensity to enter research partnership with universities
Chapter 5	(1) To analyse and compare the effects of university and cross-border co-ownerships, as well as organisational proximity on joint patent quality of Chinese firms
Chapter 6	(1) To analyse and compare the effects of different cross-border co-ownerships on joint patent quality of 80 countries covering developing countries, emerging countries, and developed countries (2) To analyse and compare the effects of different university co-ownerships on joint patent quality of 80 countries covering developing countries, emerging countries, and developed countries
Chapter 7	(1) To explore whether sharing similar knowledge bases (cognitive proximity) is conductive to high quality patent of Chinese firms (2) To investigate whether collaboration (organisational proximity) between different units of the same organization is conductive to high quality patent of Chinese firms

To address above research objectives and taking account of the nature of data, several different econometric techniques are used. For the modelling of count data (i.e. forward citations), negative binomial regression is the main technique used throughout this thesis. Traditionally, Poisson regression has been the classic solution to modeling of count data. The Poisson model assumes that the conditional mean and the variance of the dependent variable are equal.

However, the variance of the data often exceeds the mean in real world data, in which case over-dispersion occurs. This has been the case for my data. The generalization of ordinary linear regression (or generalized linear model - GLM) that allows the linear model to be related to the dependent variable through a link function. GLM has an addition parameter to handle over-dispersion in count data, such that accuracy of estimation is improved. Results for GLM are included as benchmark result.

Compared with Poisson and GLM, the negative binomial (NB) regression not only provides better fit for count data with over-dispersion issue, but also corrects omitted variable bias while simultaneously estimating heterogeneity (Hausman et al., 1984). As there is within-firm association between patents that filed by the same applicant and the presence of excess zeros, cluster robust standard errors are applied. Two variants of the NB regression are employed, i.e. negative binomial regression model with linear variance function (NB1), and negative binomial regression model with quadratic variance function (NB2). These two regressions are differed in their variance relationship with the mean. For the NB2, there is a linear relationship between the variance and the mean. For the NB1, there is a quadratic relationship between the variance and the mean. Results for the NB1 are used as main results and those for the NB2 are used as robustness test for explanatory variables.

For the modeling of dichotomous variable (i.e. the likelihood of collaborating with universities), Probit regression is employed to estimate the likelihood of firms engaging in patenting with universities. It is noted that both Probit and Logit are classic solutions to model dichotomous outcomes and they provide similar results, however the former is more popular in certain disciplines such as economics and finance.

1.4 Structure of the Thesis

The main body of this thesis is consisted of a literature review, a chapter describing the data and methodology used, and three empirical chapters investigating different aspects of joint patenting.

Chapter 2 provides a review into the motives of firms engaging in R&D collaboration, outputs of R&D collaboration, and key indicators for measuring the quality of R&D collaboration. To start with, the chapter introduces the broad context of joint patenting – R&D collaboration. It looks at different strands of theories: the resource-based view (RBV), strategic management, transaction cost economics, and organisational learning theory. Then, the chapter discusses the link between R&D collaboration and joint patenting. Finally, the chapter reviews the recent development and trends of joint patenting in emerging countries and in China.

Chapter 3 discusses the data employed by the thesis. The data is drawn from the European Patent Office's (EPO) Worldwide Patent Statistical Database, i.e. PATSTAT database (2017 Spring version). The database provides detailed and rich information on patent holders' invention activities in 35 technical fields collected from more than 100 patent offices worldwide. The data contain interesting information, such as sector and name of the patent applicant and inventor, the size of patent family, and the citations of the patent. The data not only enable me to explore the research questions in detail that most other dataset could not do, but also allow me to draw conclusions for the entire population of Chinese firms and universities.

Chapter 4, 5, 6, and 7 are the empirical chapters of the thesis. In Chapter 4, the analysis investigates the relationship between the level of technology sectors and university collaboration. In Chapter 5, the analysis explores the effects of university and cross-border co-ownerships on the quality of joint patents filed by Chinese firms. In Chapter 6, the analysis tests the effects of the same variables (i.e. university and cross-border co-ownerships) in a larger sample covering 80 countries. In Chapter 7, the analysis focuses on how proximity dimensions affect the value of collaboration between firm and university. Specifically, it looks at the roles of cognitive proximity and organizational proximity in shaping the innovation performance of firm-university collaboration. These four empirical chapters study different aspects of the same dataset, aiming to explore different aspects of joint patenting activities of Chinese firms. Chapter 8 concludes the thesis by summarizing findings, acknowledging limitations, and suggesting avenues for future studies.

Chapter 2 A Review of the Literature

2.1 Introduction to the Literature Review

This chapter briefly reviews the theoretical and empirical evidence for the motives, outputs, and performance of R&D collaboration. It is divided into three major sections. In the first section (2.2), I identify four broad reasons for entering collaboration/alliance: creating innovations, entering foreign markets, reducing demand and competition, and responding to political calls. Among these reasons, creating innovations has been found as the most cited reason for entering into alliances/collaboration. I then discuss the likely motives behind such R&D-driven alliances/collaboration in the contexts of different theories: the RBV (Barney, 1991; Wernerfelt, 1984), strategic management perspectives, and organisational learning theory. Lastly, I relate the above motives to R&D collaboration between firms, universities, and public research institutes. In the second section (2.3), I begin by explaining the importance of inter-organisational collaboration. I then discuss main innovators: research organisations (i.e. universities, and public research institutes) and firms. In the last section (2.4), I begin by arguing that joint patenting is an important form of R&D collaboration. I then explore the appropriateness of using forward citations as performance indicator of R&D collaboration.

2.2 Why Collaborate for Innovation

In this section, I discuss the reasons behind collaborative R&D and the section is structured as follows. First, the discussion begins with classifying the explanations provided by the existing body of literature. The discussion continues with motives for engaging in R&D collaboration. Then, the discussion proceeds with theories of relevance. Lastly, the discussion presents theories and the application of the National Innovation System (NIS) concept, then discusses the motives of collaboration between major innovators of the NIS, namely firms and universities.

2.2.1 Brief overview of collaboration

Previous studies have offered various explanations for inter-organisational alliances. These explanations can be broadly classified into four groups. First, creating innovations have been the most cited reason for forming alliance. It emerges that alliances are either a means of pooling complementary resources from partners (e.g. Belderbos et al., 2006) or an alternative to in-house research and development effort (e.g. Narula, 2004), for developing new products (e.g. Badir and O'Connor, 2015; Hu et al., 2017) and tackling technological conundrums (e.g. Gnyawali and Park, 2011).

Belderbos et al (2006) distinguish and analyse four types of partnerships (i.e. competitors, customers, suppliers, and universities and research institutes) on productivity growth. They confirm the positive effect of all four types of partnerships on productivity growth, but find that the magnitude and significance of impacts vary among partnership types. The positive effect of complementarity is found for competitor-customer cooperation, and customer-university cooperation.

Studying collaborations in Small and Medium Enterprises, Narula (2004) argues that even SMEs mainly rely on in-house R&D, they need to establish alliances with larger firms in order to expand markets and increase sales.

Alliances that are formed for creating innovations will be referred to as 'R&D collaboration' hereafter. As revealed in the introduction, the theme of this thesis is joint patenting, which clearly requires significant elements of research, development, or both elements (i.e. research and development) in order to yield patentable innovations. It is noted that some existing studies (e.g. Autant-Bernard et al., 2007) link joint patenting with ‘technological collaborations’. In my opinion, the term ‘technological collaborations’ itself implies more of development elements, and less of research elements during collaboration. Again, ‘R&D collaboration’ is preferred to ‘technological collaboration’ because it captures all above scenarios, which best describe different natures of joint patenting.

Second, entering foreign markets is another reason for establishing alliances. In this scenario, alliances are often referred to as “joint ventures”, which are created by two or more organisations for carrying out a productive economic activity (Harrigan, 1986). Joint ventures have been frequently associated with entering emerging markets and many scholars argued that joint ventures are better than any other entry modes (such as greenfield investments, contractual agreements, and licensing), due to the embedded risk-sharing structure that reduces individual investor’s liabilities and resources-sharing agreement that pools complementary resources from all parties (Luo, 2007). Joint ventures not only overcome market inefficiencies that prohibit the access to local resources in the presence of weak institutions, but also deter internal opportunistic acts of individual parties and capture growth opportunities (Harrigan, 1988; Kogut, 1988).

Third, alliances are used by direct competitors for reducing demand and competitive uncertainties (Burgers et al., 1993), addressing major technological challenges (Gnyawali and Park, 2011), sharing cost and risks (Das and Teng, 2000), and complying with regulatory constraints (Nakamura, 2003).

Lastly, alliances could be formed for political reasons. This is particularly salient in emerging countries, because in these countries the state has absolute control over critical resources and makes important decisions about the country’ innovation system. Empirical studies (e.g. Park and Leydesdorff, 2010) have shown that collaboration between industry and public research organisations in China and South Korea, are largely politically motivated.

Based on my review of relevant literature, it emerges that the pursuit of innovations has been one of the major reasons for entering into alliances. The reason behind this is not difficult to understand. Nowadays, as global competition intensifies, the innovativeness of a firm determines its growth and survival. Although alliance formation implies challenges, such as opportunistic behaviour, the number of alliances has witnessed a rapid growth in major developed countries, as well as in emerging countries in the past decades. For this reason, it is with interests to find out what exactly motivates firms to collaborate on R&D.

2.2.2 Motives for engaging in R&D collaboration

Collaborative R&D has been increasingly seen as an alternative knowledge acquisition strategy to internal and contract R&D. In recent years, there has been an increasing interest in the economic literature to study the motives of firms engaging in R&D collaboration. Understanding the motives helps improve current understanding on the impact of such strategy (i.e. knowledge acquisition strategy) on the innovation performance of firms that employ such strategy. To summarise, there are four broad groups of motives relevant for firms engaging in R&D collaboration.

The first set of motives is associated with the expansion of resource usage, handling uncertainties in product development and marketing, and firm’s competitive behaviour and learning tendency. First, due to increasing speed of technological change, firms may find it difficult to reap the most benefits of a technology in a short time before it becomes obsolete (Tsang, 1998). If firms want to make further use of the technology, one option is to invest in a second industry and set up production lines; another option is to expand production in the same industry abroad. Both options require resources that most firms do not possess. Second, due to concerns over unclear prospects of new products as well as the reluctance to sink R&D cost, firms, in particular technology giants, choose to diversify their resource portfolio in order to reduce risks. Forming alliances is an effective way of solving above issues occurred during process of expansion, and product and market development.

The second group of motives is related to market access and technology advancement. At the local level, one possible reason associated with alliance formation is likely to be monitoring environmental changes whist creates new markets/products/processes.

Another possible reason may stem from competition. A strategic alliance may be used to defend current strategic positions against external forces. Through combination of resources and capabilities, a strategic alliance may reduce competition through allying with existing competitors.

At the international level, forming alliance is associated with expansion of production. Given the complications behind different mode of entry into a foreign market, Glaister (1998) suggests that strategic motive plays an important role in determining a firm’s choice of entry mode.

In addition, Contractor and Lorange (1988) suggest that for many firms, their initial overseas expansion reply on strategic alliance, because strategic alliances offer considerable time savings for firms with limited overseas production capacity or limited knowledge of foreign markets.

To be successful in alliances, learning should become an organisational routine. Successful alliances evolve through a sequence of ‘learning - re-evaluation - re-adjustment’, whereas unsuccessful alliances operate without learning or have problems of learning (Doz, 1996).

In other cases, alliances are formed for covering up the secret learning of capabilities from partners when formal consent of technology transfer is absent. This is because technological capabilities are usually tacit knowledge that is not easily assessable and requires lots of interaction. Another motive is concerned with the need to acquire knowledge from other organisations in other industries.

The third group of motives is related to the sharing and development of research among participating firms. Due to the increasing complexity of new technologies and cross-fertilisation of scientific disciplines and technology fields, no firms, even the large ones, are capable of succeeding in every technological filed in terms of reaping benefits out of innovations (Hagedoorn, 1993). For this reason, the necessity for firms to monitor the development of technologies has reached an all-time high.

At the same time, the costs to conduct R&D activities have been increasing in a large number of technology fields. In order to reduce uncertainties/risks, firms tend to choose to form alliances for obvious reason. Collaboration can reduce risk/uncertainties in a number of ways, include spreading risks associated with technology development, and reducing risks associated with market. Furthermore, Hagedoorn (1993) points out that it is more appropriate to think of the sharing of R&D in terms of reduction of uncertainty rather than reduction of risks, because uncertainty is associated with unknown likelihood of an event that has no probability distribution, whereas risk is just the opposite.

The fourth motive is to do with learning tendency that result from competitive behaviour. On the one hand, firms see inter-firm collaboration as a way to reach external expertise, to develop internal competencies and competitive advantages. On the other hand, firms have the tendency to keep their valuable assets internally and permanently, and prevent their assets from decaying. Collaboration could be seen as retaining and enhancing knowledge for future deployment at the expense of sharing part of its current knowledge (Das and Teng, 2000; Nelson, 1982). The extent to which a firm can learn from an alliance is dependent on the firm’s capability to imitate and absorb others’ core knowledge – known as ‘absorptive capacity’ (Cohen and Levinthal, 2000).

2.2.3 Theories of relevance

Motives that are concerned with usage of resources and competitive behaviour (the first set of motives) can be explained by the RBV. The RBV takes an internal perspective, arguing that resources are crucial to superior performance. Alliances formation is the seeking of complementary resources and the handling of existing resources. Seeking complementary resources (technological capabilities, technologies, and skills) usually occurs when firms lack in-house capacity to develop innovations. Handling of existing resources is less discussed in the literature however it is no less important. Alliance could be an option for extending the usage of a certain resource (usually technology) for further exploitation.

Motives that are related to market access, technology advancement, and cost sharing (the second and third set of motives) can be explained by strategic management literature. The strategic management scholars emphasize the role of strategic intent in alliances. Such alliances are referred to as ‘strategic alliances’ in the literature. Strategic alliances may or may not involve collaboration on R&D: motives like technology advancement and cost sharing may be concerned with R&D collaboration; others like entering new markets may not necessarily involve R&D collaboration at all.

Motive that is concerned with the learning tendency (the fourth set of motives) can be explained by organisational learning perspectives. Interestingly, there are overlaps between the perspectives and the RBV. For instance, the organisational learning literature (e.g. Sakakibara, 1997; Zhang and Baden-Fuller, 2010) suggests that a key motive of alliances is to seek complementary knowledge or skills for building up firm’s own internal competencies. Similarly, learning as a strategic motive in alliances has also been spotted by the strategic management scholars (e.g. Tsang, 1999). Studying learning in alliances, Rothaermel (2001) suggest that the orientation of organisational learning is different in exploration- and exploitation- driven alliances.

2.3 Who Collaborate for Innovation

In this section, I present theories and the application of the National Innovation System (NIS) concept, then discusses the motives of collaboration between major innovators of the NIS, namely firms and universities.

Industrial firms, universities, and public research organisations are important innovators in a NIS. Popular theories of NIS include the Triple Helix model (Etzkowitz and Leydesdorff, 2000), the dynamic social network, and the institutional theory. The key assumption behind the Triple Helix model is that synergies of three innovators can lead to changes in the national innovation system in terms of lock-ins and path dependencies. This model has been used for policy advice about network development among innovators in NIS. The dynamic social network literature (e.g. Agapitova, 2005) argues that the quality of relationships between actors influences the viability of the NIS. Variables such as trust and proximity among actors play important role in the creation of knowledge and economic value. In an empirical study, Audretsch et al. (2004) showed that spatial proximity of universities enables dynamic exchange of capabilities to be sustained in a NIS. Like many other theories originated in the West, many studies on NIS have been dealing with the developed countries.

Discussing the applicability of the NIS concept to transition countries, Kitanovic (2007) argues that the extent to which a transition country can catch up and sustain economic development depends on its technological capabilities. The level of these capabilities, she argues, is influenced by the relationships with other actors in the NIS. This argument resonates with that of Agapitova (2005), who suggests that innovation and technological change is a technological and social progress resulting from communication networks. Kitanovic (2007) argues that know-how and know-who are the most important types of knowledge for transition countries, as know-how involves the interpretation of increasing complex information, which leads to the formation of industrial networks; know-who refers to the ability to cooperate and communicate with others. Clearly, these two types of knowledge are rooted in practical experience and social interaction. In other words, both types of knowledge involve tacit knowledge that are not easily transmitted and but can be learned from practice and interaction. Due to this reason, Kitanovic (2007) concludes that transition countries should strengthen linkages among actors of NIS for developing social and technological capabilities. To sustain these capabilities for further development, transition countries need to learn by feedback and by systematic searching. In summary, the selected NIS literature highlights the importance of networking and interactions within the NIS, which is crucial to the economic development of transition countries.

Based on the literature review, I argue that collaboration between firms tend to be associated with expansion of resource usage and monitoring of technology development and environmental changes. Indeed, due to the shortening cycle of technology development resulting from competition, firms may find it difficult to appropriate the benefits of a technology before it becomes obsolete. The decision to invest in a second industry or to expand production abroad, is largely associated with firm's intention to further exploit certain technologies. Second, in the presence of intense competition, firms may collaborate with direct rivals on R&D, because collaboration is a defensive mechanism to protect firms' current positions, and a strategic move to reduce competition though collusion. In addition, firms can learn more about strategies and capabilities of their partner through collaboration. Such learning behaviour may occur in collaboration between competitors, or between firm and university/PRI.

2.3.1 The importance of collaboration across boundaries

From the perspective of open innovation theorists (e.g. Chesborough, 2006; Laursen and Salter, 2005), knowledge creation and innovations require the combination of diverse, heterogeneous, and complementary capabilities of different partners. Since tacit knowledge is idiosyncratic to firms that created it, a firm is unlikely to be benefited from the collaboration if there is no shared technological experiences or similar knowledge bases with its collaborator(s). In the view of proximity theorists (e.g. Boschma, 2005; Balland et al., 2015), organisations that share identical knowledge bases can learn from each other quickly and efficiently. The literature recognises that there are general knowledge and specific knowledge. For instance, Cohen and Levinthal (2000) state that firms need to be similar enough in knowledge bases to be able to recognise the opportunities offered by collaborators, but different enough in knowledge used in everyday functioning in order to learn more from collaboration. It is interesting to test whether this assumption holds for my data.

In addition to a common knowledge base that is important for bringing firms together for interactive learning, a capacity to coordinate the exchange of complementary knowledge within and between organisations (Boschma, 2005) is also necessary.

In large organisations, heterogeneous strategies, incentives, and capabilities of units can make technological integration a very challenging task (Frost and Zhou, 2005). Furthermore, because knowledge creation and innovations often involve uncertainty and opportunism, collaborators with similar knowledge base and company culture appears to be favourable to many firms. Centralized coordination that brings together different units (Lawson and Lorenz, 1999) within an organisation entity can effectively facilitates the transfer of complex knowledge between different sub-units (Hansen, 1999). Nevertheless, there are opposing views that too much organizational proximity could affect learning and innovation by reducing flexibility (Capaldo and Petruzzelli, 2014). The mixed findings on the effect of organisational proximity is another motivation for conducting empirical analysis.

2.3.2 Collaboration between key innovators and innovation performance

Prior research suggests that interaction with different type of firms, including competitors, suppliers, and customers, may bring different outcomes. Collaborating with suppliers is one important way for improving solutions, creating new methods, and reducing costs for product development (Bonaccorsi and Lipparine, 1994). Suppliers may help a firm to identify the technical problems and offer solutions, thus shorten the product innovation process (Kessler and Chakrabatri, 1996).

Customer collaboration is another important way for firms to improve product innovation performance, as customers may help identify market opportunities, reduce the likelihood of poor design at the early stages of product development (Tsai and Wang, 2009), and gain access to knowledge that manufacturers may not immediately possess.

Collaborating with competitors is an important way of reducing time in product innovation. Literature (e.g. Tsai and Wang, 2009) shows that competitor collaboration is not uncommon in industries with rapid technology development and short product cycles, since the risks and uncertainties associated with the technology under development and market response are usually too huge to be absorbed by a single organisation. Competing firms are active innovators of similar technologies, thus collaboration shortens the length of innovation. Empirical evidence (e.g. Belderbos et al., 2014) shows that collaborating with competitors is both negatively associated with patent quality and a firm’s market valuation.

Compared with collaboration between firms, collaboration between firm and research organisations (i.e. universities and PRIs) is primarily associated with reduction of uncertainties in innovation development and leaning tendency. Due to the increasing complexity of technologies, firms, even those technological giants find it difficult to appropriate the most out of every field in which they operate. Moreover, since R&D activities are rising in many industries, bearing all the costs seems rather risky, especially when new product is under development and there are uncertainties about the technical aspect and marketing. The learning intent of firms, is also common in collaboration between firm and university/PRI. In many countries, research organisations, are highly regarded in their achievement in basic science, whereas the majority of firms have been known to focus on the ‘applied’ side of science. Collaboration with research organisations enables firms to absorb scientific knowledge, which is the key to innovation breakthroughs.

Empirical studies report mixed findings on the effect of involvement of research organisations on product innovation. Belderbos et al. (2004) found that university cooperation not only produces good public spillovers, but also improves firms’ innovative sales. Spencer (2003) suggested that universities help facilitate a technological breakthrough to turn into a commercial product. Hu and Mathews (2008) showed that university R&D as a driver of patenting has a positive impact on the China’s Gross Domestic Product (GDP). Baba et al. (2009) found that collaborations with university scientists can predict the R&D productivity of the firm in Japan. Kafouros et al. (2015) confirmed that collaborations with universities improve firms’ innovation performance but over-unitilisation of university knowledge hinders firms’ innovation performance. However, Lhuillery and Pfister (2009) found that firms conducting research with universities are more likely to face delay or even ‘cooperation failure’ than with suppliers or customers due to the divided opinions in managing deadlines, technological distance, and intellectual property rights. Monjon and Waelbroeck (2003) found a negative relationship between collaborations with universities and product innovation performance, using data from France.

2.4 How to Measure Performance of R&D Collaboration

In China, joint patenting is an important channel that R&D interaction among the business sector, universities, and public research organisations take place (Schaaper, 2009). Joint patent, or co-patent, is an important output of inter- or intra- organisational R&D collaboration.

The literature suggests that the decision to pursue joint ownership of patents rights may be due to a variety of reasons. First, joint patents may be anticipated outputs of formal collaborations between partners (Hicks, 2000). In particular, partners will resort to joint patenting when the innovation under development has the potential to be a core competency for one partner and a risk that is caused by abuse of IP rights by the other partner (Teng, 2007).

Second, joint patents may be unanticipated outputs of small scale, informal collaborations between firms (Belderbos et al., 2014; Hagedoorn, 2003) that are difficult to divide the intellectual property between the participants. Third, firms that engaged in joint patenting in the past (Hagedoorn, 2003) or have history of successful alliance (Kim and Song, 2007) are more likely to engage in joint patenting for innovations.

For above reasons, joint patent may capture only a subset of collaborative efforts (Briggs, 2015). Yet, it remains an important indicator that signals the quality of collaboration and a potential window to investigate firm openness and performance.

Existing studies on joint patenting do not hold consensus on its effect on organisational performance. Hagedoorn (2003) argues that joint patenting is a second-best strategy that firms should avoid. Belderbos et al. (2010) found a negative relationship between joint patenting and firm’s market value. By contract, more recent research shows that joint patenting is more successful than individual patenting in terms of quality enhancement. Briggs (2015) finds that co-ownership with universities enhances patent value in the long run. Belderbos et al. (2014) found that co-ownerships with vertical partners and universities correspond to high quality innovations.

Despite the indeterminate effect on firm performance, together with potential legal and management challenges as suggested by scholars, joint patenting has witnessed a steady increase in major patent jurisdictions. Compared with above indicators of R&D collaboration, joint patent allows researchers to measure the performance of R&D collaborations, via various aspects of patent-level information such as forward citations, size of patent family, backward citations, and patent claims. The next section discusses the pros and cons of forward citations.

2.4.1 Forward citations

In this thesis, forward citation is a major measure of collaboration performance, or joint patent quality. Forward citations refer to the number of patent applications citing a previous patent as an influential prior art (Briggs, 2015). Forward citations received by a given patent play a similar role to that of citations in academic publications as an indicator for the importance (Blind et al., 2009).

The assumption behind forward citation analysis is that highly-cited patents contain important technological innovations that facilitate spillovers and form the basis of many later inventions (Acosta et al., 2012; Briggs, 2015; Thomas and Breitzman, 2006), so they are good proxy for technological importance (Fischer and Leidinger, 2014) as well as economic value (Hall et al., 2000).

From the technological perspective, Blind et al. (2009) found that patent that used for protective and defensive purposes receive higher number of citations. Barbera-Thomas et al. (2011) show that forward citations are valid measures of knowledge flows within a network.

From the economic perspective, a large body of empirical work have reported a positive relationship between forward citations and economic value at both patent level and firm level. Using a survey, Harhoff et al. (1999) show that there is indeed a positive relationship between forward citations and patent’s own economic value. Hall et al. (2005) demonstrate a positive relationship between forward citations and stock market valuation of the firm’s intangible stock of knowledge. “At the European Patent Office, examiners make the ultimate decision on which patents will be included as references to the prior art related to the submitted application” (Blind et al., 2009). These references to the prior art indicates the patentability of the submitted applications and the basis on which they are built. A growing body of empirical research indeed confirm the positive relationship between forward citations and patent quality. Fischer and Leidinger (2014) found that receiving one more forward citation within the first five years of publication can increase patent value by $14,224.

Nevertheless, forward citations are not without drawbacks. First, citations take time to accumulate (Breitzman and Thomas, 2015; Nemet and Johnson, 2012), resulting to truncation issues. Acosta et al. (2012) and Gittelman (2006) empirically show that younger patents are less likely to be cited than older patents. Second, as innovations are mostly built on previous technologies, firms tend to include their previous patents as reference to prior art, thus introducing the self-citation bias.

To overcome the first drawback, I include only forward citations received within five years of the first publication date. In addition, year dummies and technological field dummies are also added in order to control for time effect and propensity bias. This will ensure that all patents in the dataset have equal length of time to be cited by later inventions. The second weakness, i.e. self-citation, is not a major concern here, as empirical evidence (Hall et al., 2005) has suggested that self-citations are also positively related to patent value, hence in my thesis forward citations are self-citation inclusive. In summary, the advantages of using forward citations outweigh the disadvantages, making forward citation a suitable indicator for measuring quality of collaborative R&D, which is the focus of this thesis.

2.5 Overview

In this chapter, I discuss issues ranging from the motives of R&D collaboration, actors of R&D collaboration, and performance indicator for R&D collaboration. The discussion of motives of collaboration begins with the mapping of key arguments with the RBV, strategic management perspectives, and organisational learning theory. Then, the discussion extends to players of collaboration: research organisations and firms. I discuss the importance of collaboration for innovation, and explore different types of collaboration and innovation performance. Lastly, I highlight the significance of joint patenting and forward citations as an appropriate measure of R&D collaboration. The next chapter is focused on data.

Chapter 3 Data Source

3.1 Purpose of the Chapter

In this chapter, I introduce the data used in the thesis. It covers the reason for using the database, the process of setting up the data set, and the key variables.

3.2 PATSTAT Explained

The thesis draws on data from EPO Worldwide Patent Statistical Database (also known as PATSTAT), which is one of the most prominent databases that offer bibliographic patent data for more than 100 patent offices. The main data source of PATSTAT is the EPO's master bibliographic database, DOCDB, which contains international patent classifications, citations, titles, and all bibliographic data. PATSTAT is updated twice a year (spring and autumn). The thesis is drawn on the 2017 Spring version of the database. The data used cover the period 1985-2016.

PATSTAT is one of the most widely used patent databases by scholars in economics and social science disciplines. The database provides detailed and rich information on applications submitted, in terms of applicants, inventors, publications, patent families, technological classifications, citations, and so on. It is understood that there are at least two other patent databases that can offer similar services: the NBER patent database of the U.S. and the IIP patent database of Japan. In comparison with these two databases, PATSTAT covers information such as priority and international technological classifications that are not available in the other two databases, giving users of PATSTAT greater freedom in their analysis. In the United States Patent and Trademark Office (USPTO) system, all relevant citations are legally required in the application to avoid potential legal issues. However, this often results in a tendency that quotes references even if they are only remotely related to the application, subsequently, noises are introduced when citations are used as proxies for patent quality. In the EPO system, patent examiner is ultimately responsible for including all relevant prior art for the submitting application, making the database a more robust source of patent statistics for potential users.

However, PATSTAT is not without disadvantages. First, applicants' and inventors' addresses, which are crucial for geographic analysis, are largely missing. Nevertheless, the impact of this disadvantage is negligible on this thesis because geographic analysis is beyond the focus of this thesis. Second, due to geographic and cultural proximities between EPO and European countries, it is expected that PATSTAT attracts more patent applications from European countries than from the rest of the world. For this reason, random checks were carried out between PATSTAT and the patent database of State Intellectual Property Office (SIPO) of the P.R.C. First, I retrieved a subsample (50 joint Chinese patent observations) from PATSTAT. Then, I manually matched patent from PATSTAT with those from SIPO database, using publication number of patent. All the observations in the subsample are found in SIPO database. It is, however, unrealistic to reverse the random checks (i.e. using publication numbers of joint patents from SIPO to test the coverage of PATSTAT), because SIPO data cannot be downloaded for further statistical analysis. Geographical bias is a common issue for national patent offices. Compared patents from the USPTO and EPO, De Rassenfosse et al. (2013) find that USPTO has stronger geographic bias than EPO. Furthermore, the value of patent applications filed to the USPTO is relatively lower than those filed to the EPO. From this point of view, EPO appears to be a better source for studying patenting activities. The next section explains the setup of the dataset.

3.3 Setup of datasets

Two sets of data are used in the empirical chapters of the thesis. The two data sets differ in two aspects. The first difference is geographical coverage. The first data set includes all countries (80) that have record of joint patent filings in the EPO. The second data set is a subset of the first one, which contains joint patent applications for a single country – China. The second difference is time frame. The first data set includes joint patent applications recorded by the EPO between 1987 and 2016. The second data set includes joint patent applications between 1985 and 2010 and explanation is to be followed shortly.

To answer the research questions relevant to joint patenting activities of Chinese firms, I adopt the following procedures to clean the second data set. First, since the interest of this thesis is firm innovation, the first criteria specifies that any joint patent application should have at least one applicant that is operated in the business sector. As a result, joint patents that stemmed from university-university/university-research institute/research institute-research institute collaborations were excluded from the sample.

The next step specifies that country residence of one applicant should be China. In effect, all the joint patent fillings made by companies resided in China were included. The last step specifies that the year of filing should be between 1985 and 2010. 1985 is regarded as the beginning of China's patent growth as it is the founding year of China's national patent office, i.e. SIPO. In total, 5286 joint patents[2] were retrieved using above criteria, covering 766 applicants and 782 co-applicants during the period of 1985-2010.

Table 3.1 shows the number of patent applications by year. As it illustrates, 1985 witnesses the filing of first joint patent from China. There was no significant increase for joint patents between 1985 and 1996. The rapid growth of joint patents begins in 2001, when there was a significant 65 per cent increase from the previous year. In 2003 there is a slight decrease in

[2] Note that this is the number of patents with valid country codes.

the number of filings, however growth quickly resumes and a 45 per cent upsurge was observed in 2004. The number of filings continues to grow for the next four years (2005-2009). In 2010, the number starts declining. The drop in the numbers is consistent with the trend observed in the world data set (used in Chapter 5).

Table 3.1 also shows the number of applicant firms by year. It emerges that, before 2001, joint patenting activities were the business of a handful of firms. By the time of 2001, there is a significant increase in the number of participating firms and this trend has been continuing till 2010.

Table 3. 1 Number of firms and joint patents by year.

Year	Number of firms	Number of joint patents filed by firms	Joint patents in percentage
1985	1	2	0.04%
1986	3	5	0.09%
1987	2	6	0.11%
1988	10	13	0.25%
1989	12	18	0.34%
1990	9	11	0.21%
1991	10	11	0.21%
1992	4	8	0.15%
1993	8	8	0.15%
1994	3	12	0.23%
1995	10	17	0.32%
1996	3	14	0.26%
1997	8	27	0.51%
1998	18	47	0.89%
1999	12	45	0.85%
2000	19	45	0.85%
2001	34	127	2.4%
2002	55	135	2.55%
2003	52	130	2.46%

2004	80	236	4.46%
2005	96	314	5.94%
2006	108	402	7.6%
2007	154	628	11.88%
2008	181	993	18.78%
2009	227	1,137	21.51%
2010	262	895	16.93%
Total	766	5286	100%

Table 3.2 lists top 10 applicants with the corresponding number of joint patents filed. As the table demonstrates, joint patenting activities in China are dominated by multinational firms, prestigious research organisations, and large state firms. For instance, the multinational firm Foxconn Group and its branches (e.g. Hongfujin Precision Industry (Shenzhen) Company, Fuzhun Precision Industry (Shenzhen) Company, Futaihong Precision Industry (Shenzhen) Company) accounts for a considerable number of joint patents. Tsinghua University, one of the most prestigious universities in China, claims the second place in the ranking. China Petroleum & Chemical Corporation, the largest SOE, ranked fourth.

Table 3. 2 Top 10 applicants in the sample.

Ranking	Organisation	Number of joint patents	In percentage
1	FOXCONN	985	18.63%
2	TSINGHUA UNIVERSITY	704	13.32%
3	HONGFUJIN PRECISION INDUSTRY (SHENZHEN) COMPANY	698	13.20%
4	CHINA PETROLEUM & CHEMICAL CORPORATION	682	12.90%
5	NUCTECH COMPANY	292	5.52%
6	FUZHUN PRECISION INDUSTRY (SHENZHEN) COMPANY	269	5.09%
7	RESEARCH INSTITUTE OF PETROLEUM PROCESSING, SINOPEC	244	4.62%
8	ALCATEL LUCENT	190	3.59%
9	CHINESE ACADEMY OF SCIENCES	166	3.14%
10	SHENZHEN FUTAIHONG PRECISION INDUSTRIAL COMPANY	155	2.93%

3.4 Variables

Table 3.3 lists the variables that extracted from PATSTAT, and the ones that constructed for enabling investigation of the research questions. The key variables are explained in detail below the table.

Table 3. 3 Variables and definitions.

Source	Variable	Definition
PATSTAT	Application identification number	A unique identification number assigned to a patent application.
	Year	Year of the first publication
	Technologies	Number of technology fields that a patent application covers
	applicants	The number of applicants specified on the application document
	inventors	The size of invention team
	Patent family	The size of patent family
	Forward citations	Number of forward citations received within five years of first publication
	Backward citations	Number of prior arts referenced by a patent application
	Non-patent literature (NPL) citations	Number of science literatures referenced by a patent application
	Identification number of applicant	A unique number EPO assigned to applicant
	Name of applicant	The harmonized name of applicant[3]
	Identification number of co-applicant	A unique identification number EPO assigned to co-applicant
	Co-applicant name	The harmonized name of co-applicant
	Country of residence of co-applicant	The country that the co-applicant resides in
	“Sector” of applicant	The sector of applicant (e.g. company, university, hospital)

[3] See: http://www.oecd.org/sti/inno/43846611.pdf

	“Sector” of co-applicant	The sector of co-applicant (e.g. company, university, hospital)
Author’s own construction	High-technology sector	Dummy variable, operationalized as 1 if a given patent is classified as a high-technology patent, and 0 if otherwise
	Medium-high technology sector	Dummy variable, operationalized as 1 if a given patent is classified as a medium-high technology patent, and 0 if otherwise
	Medium-low technology sector	Dummy variable, operationalized as 1 if a given patent is classified as a medium-low technology patent, and 0 if otherwise
	low technology sector	Dummy variable, operationalized as 1 if a given patent is classified as a low-technology patent, and 0 if otherwise
	Foreign-invested enterprise	Dummy variable, operationalized as 1 if partner is a foreign-invested enterprise, and 0 if otherwise
	SOE	Dummy variable, operationalized as 1 if partner is a SOE, and 0 if otherwise
	privately-owned enterprises (POE)	Dummy variable, operationalized as 1 if partner is a private enterprise
	Ethnic Chinese firm	Dummy variable, operationalized as 1 if partner is an ethnic Chinese firm (that comes from Hong Kong, Taiwan, or Macau)
	Cross-border partner	Dummy variable, which is coded as 1 if partner is originated from countries other than China, and 0 if otherwise
	University partner	Dummy variable, which is coded as 1 if partner is a university, and 0 if otherwise
	Organisational proximity	Dummy variable, which is coded as 1 if applicant and co-applicant belong to the same company, and 0 if otherwise

3.4.1 Number of technology fields

The variable is measured by the number of 4-digit International Patent Classification (IPC) listed on the patent document. Empirically, this is a method of measuring the scope of a patent. The variable captures the technological breadth of patents and therefore can be important indicator for economic and market value. It has been empirically demonstrated that broad patents are generally more valuable than narrow patents (Lerner, 1994), from that firms should develop the capabilities to be able to jointly manage the process of technology span search so as to increase the value of joint R&D.

3.4.2 Number of inventors

The variable refers to the number of inventors listed on the patent application. It is possible that the size of the research team is conductive to innovative performance. Firstly, it is believed that the size of a research team can capture the intellectual resources invested in developing technology (Belderbos et al., 2014). The larger the size of a research team, the faster and greater diffusion of knowledge, leading to different citation patterns. Secondly, it has been suggested that firms that possess external linkages are more innovative than those that do not (Laursen and Salter, 2006), as these linkages bridge the gap between internal capacity and external knowledge, leading to more valuable innovation outcome (Leiponen and Helfat, 2010; Love et al., 2013).

3.4.3 Number of forward citations

A forward citation, also known as a citing document, is the document that cites a given patent publication published earlier. In general, the more the number of forward citation received, the more significant the technological impact of the cited patent on the development of the citing patents. The variable is widely used in innovation literature for a number of purposes, including measuring firm innovative performance (Sampson, 2007, Singh, 2008), innovation impact (Miller et al., 2007), innovation output (Singh, 2008), and knowledge flows (Crescenzi, Nathan and Rodríguez-Pose, 2016). Trajtenberg (1990) found that forward citations are positively and significantly correlated with independent measure of returns from innovation. Hall et al. (2005) found that compared to those less frequently cited, patents with high citations are more likely to be profited from economic activities. To control for the time truncation effect and avoid possible bias towards older patents[4], only forward citations received within five years of a patent invention's first publication is considered.

3.4.4 Number of backward citations

Backward citations are referred to the references made to prior art, which could include both patents and scientific literature. In the patent value literature, backward citations are used to indicate the technological breadth of an invention (Harhoff et al., 2003), the knowledge spillovers that allow follower firms in the field to catch up with the leading firms through working around past patents (Nadiri, 1993). Literature suggests that while a higher number of backward citations indicates a less novel and more applied invention, a lower number of backward citations indicates a less incremental and more basic invention (Thursby et al., 2009).

3.4.5 Number of NPL citations

This variable refers to the number of references made to the non-patent literature, usually scientific articles. The variable can proxy the linkage between the technological development

[4] Since there is usually a lag between the application and the publication/granting date, newer inventions may be less likely to be cited due to lack of exposure.

and scientific research. The higher the number of non-patent literature cited in a patent, the closer a patent links with basic and apply research. Lo (2010) shows that more than 90 percent of references included in genetic engineering patents that granted to research organisations were non-patent literatures, suggesting that there is a strong dependence of the technology on scientific research. The variable can also signal the effort made by patent applicant on knowledge searching, which is believed to have a positive impact on the innovative performance. I believe that the scope of knowledge searching influences patent performance. The more non-patent literatures cited in a patent, the closer a patent links with basic and apply research.

3.4.6 Technology field dummies.

The World Intellectual Property Organisation (WIPO) specifies five patent fields for patent inventions, including chemicals, mechanical engineering, electrical engineering, instruments, and other fields. It is expected that the citation intensity of these patent fields differs due to different intensities of filing. I use a concordance table developed by Schmoch et al. (2003) to link the IPC code listed on the patent document with patent field, as identified by WIPO.

3.4.7 Patent claims

Publication claims refer to the scope of the protection sought in a patent application. In the literature, the number of patent claims is an important variable in the patent value literature. Studying trends in claims awarded to inventors in France, Japan, the United Kingdom (UK), and the US, Tong and Frame (1994) suggest that claims is positvely correlated to national technologcial capacity. Lanjouw and Schankerman (2001) show that there is a positive relationship between the number of the claims and the probability for a patent to be disputed.

Sertzi (2013) found that the number of cliams is positive related to forward citations, which is the proxy for patent value.

3.4.8 Patent family size

Patent family size is defined as the number of jurisdictions for which patent protection was granted, signalling the patent applicant's expectation of opportunities to use the patent in different international markets (Torrisi et al., 2016). Like forward citations, patent family size has been seen as a robust and consistent indicator of the value of patent rights (Fischer and Leidinger, 2014; Harhoff, Scherer, and Vopel, 2003; Martinez, 2011) at the firm level (Neuhausler and Frietsch, 2013; Wakelin 1998). The idea behind family size analysis is that the applicant is willing to bear additional costs for the expansion of patent protection in foreign markets. Such additional costs usually include translation fees, patent attorney's filing fees, and examination fees (Fischer and Leidinger, 2014; Martinez, 2011). For this reason, it is believed that the applicant only files the invention abroad if he or she expects a profit from the sale of a given technology. In addition, the more important the technology to the applicant, the more broadly the technology will be patented (Wang, 2007).

Analysing the relationship between patent family size and patent value, Putnam (1996) found that the distribution of patent value is highly-skewed: the economic returns of top five per cent of inventions are equivalent to half of the total value of private R&D in the sample. Furthermore, the most valuable patents would seek protection in major developed countries. Using real-world auction data to test predictions on patent value indicators, Fischer and Leidinger (2014) reveal that the family size of sold patents is significantly higher than that of unsold patents and that add an additional family member increases the patent value by $750. One potential weakness of patent family size is related to the propensity to internationalisation in different technological fields. Empirical evidence from Harhoff et al. (2003), and Neuhausler and

Frietsch (2013) suggest that family sizes in the area of information technology, chemicals, and pharmaceuticals are significantly higher than, for example, machinery and automobiles (Blind et al. 2003). Fortunately, this weakness can be dealt with by including a technology field dummy.

3.5 Econometric methods

For the count dependent variables (chapter 5, 6, and 7), a range of regression models are employed to fit the data. To begin with, I apply the Ordinary Least Squares (OLS). The application of OLS ignores the count nature of the data but uses robust standard errors. Clearly, the OLS estimator is inappropriate, since the conditional mean function of the OLS may take negative values and the variance function is specified as homoscedastic. Consequently, applying the OLS to count data would lead to inconsistent estimates and wrong variance matrix. Nonetheless, it is useful to start with the OLS estimator because it gives results similar to estimators using the exponential mean.

Poisson regression model is the simplest regression model for count data. The Poisson data-generating process specifies that conditional mean and variance are equal (defined as equidispersion) for valid statistical inference. I apply Poisson quasi-maximum likelihood estimator with robust standard errors (PQMLE) to fit the data.

For nonlinear models (i.e. count models), it is more straightforward to interpret the results via the interpretation of marginal effects than direct interpretation of model coefficients. For this reason, I look at the average marginal effects (AME), which first aggregates all individual responses and then calculates the average response.

In real-life data, this property is frequently violated: in many cases the conditional variance is greater than the conditional mean (defined as overdispersion). The analysis shows that the variance is approximately ten times the mean, suggesting that the data are overdispersed. For this reason, Poisson quasi-generalized pseudo-maximum likelihood estimator with robust standard errors (PQGPMLE) is employed. PQGPMLE relaxes the assumption about conditional variance, hence is appropriate for modelling overdispersed data.

However, PQGPMLE is still less attractive since it uses a quasi-likelihood rather than a maximum likelihood method. For overdispersed data, mixture regression models appear to be better options. For the main result, I apply two mixture models: NB1 and NB2. It is useful to distinguish between the two models. Variants of NB1 and NB2 are Poisson-gamma mixtures that better fit overdispersed data. The two has different variance relationships with the mean: for the NB2, there is a linear relationship between the variance and the mean; for the NB1, there is a quadratic relationship between the variance and the mean.

Chapter 4 The Propensity of Technological Collaborations

4.1 Introduction

For a long time, the innovation performance and innovation behaviour of different manufacturing sectors have been the interests of the academia. In order to provide benchmark for comparing productivity growth and competitiveness across nations, the OECD divides manufacturing industries based on aggregate R&D intensities (Hatzichronoglou, 1997). The sectoral approach classifies manufacturing industries into four categories: 1) high-technology, 2) medium-high technology, 3) medium-low technology and 4) low-technology[5].

Nowadays, the globalization and the intensification of competition in markets around the world are increasingly based on innovations (M'Chirgui, 2009). It is argued that in higher technology sectors where innovations are based on scientific knowledge, the innovation behaviour of firms is closely linked to the development of technology (Becker, 2004). In these sectors, continuous innovations are critical to survival and competitiveness because of rapid change in technologies and short life cycle of products. In order to stay current with the latest technological development, technological collaboration has increasingly become a strategic option for many firms in different level of technology sectors. By collaborating on technologies, firms can better cope with increasingly shortening technology cycles, cost, and complexity of technological developments (Tsai and Wang, 2009).

The innovation system literature emphasizes the importance of interactions among key players, including firms, universities, and government. Due to the importance of high-technology in national economic growth (Schartinger et al., 2002), university as an important source of

[5] Alternatively, Pavitt's (1984) taxonomy of innovating firms can be used here. Pavitt's taxonomy divides firms (both manufacturing and service) into four broad categories, including supplier dominated firms, scale-intensive firms, specialized suppliers, and science-based firms.

scientific knowledge has attracted lot of attention and discussion from the academia. However, few studies assess the outcome of collaborations between universities and different technological sectors. This research empirically investigates the problems by analyzing Chinese firms' propensity to collaborate with universities using firm-level data.

The remainder of the chapter is organized as follows. Section two reviews relevant literature and develops hypotheses of the study. Section three discusses source of data, variables, econometric models, and choice of estimation method. Section four reports results of regression models. Section five discusses the results and section six concludes the chapter.

4.2 Literature Review and Hypotheses Development

Due to the increasing complexity of knowledge in medium-high (MHT) and high technology (HT) sector, firms may attach greater importance to knowledge from beyond their boundaries (De Faria et al., 2009). The decision to collaborate on innovations could be influenced by a number of factors. Firstly, prior evidence (Hagedoorn, 2003) suggests that the strength of intellectual property rights protection of a sector is closely related to its propensity to engage in joint patenting. My data suggests that joint patenting plays a significant role in sectors with strong intellectual property rights protection such as oil and gas, and pharmaceuticals (i.e. MHT and HT sectors), and plays little role in sectors with weak intellectual property right protection, such as textile and food (i.e. LT and LMT sectors). The propensity to engage in joint patenting also depends on the locus of innovation. It is expected that sectors are characterized by rapid technological change value radical innovations highly, thus are more likely to rely on external sources for innovations.

Secondly, MHT and HT firms are usually in possessed of ready-to-use proprietary technological knowledge (Colombo et al., 2006). The longer these firms operating in the industries, the more experienced they become and hence are in a better position to deal with the transaction costs and appropriability hazards associated with partnerships (Teece, 1986). This makes them attractive to potential research partners.

Thirdly, the intensity of in-house R&D stimulates the probability of joint R&D activities with other firms significantly (Becker and Dietz, 2004). MHT and HT firms invest significantly more resources in R&D activities than medium-low technology (MLT) firms due to the need to stay informed for the cutting-edge technologies. These MHT and HT firms are technology gatekeepers, which means that they are interested in creating products and services that are unique to the market users. To bring down the costs and minimise the risks associated with such innovations, engaging in R&D cooperation is a natural and attractive option.

Fourthly, Link et al. (2002) find that when MHT and HT firms experience a decline in competitive performance, they tend to rely more heavily on research collaborations. It is understood that in MHT and HT sectors, especially in those where technology maturity is high, firms that do not innovate persistently would be driven out of the competitive market. Collaboration can shape competition by improving firm's comparative competitive position. Collaboration exposes firms to a larger network, which can enhance efficiencies by coordinating necessary resources at lower costs. By dividing technological specialisation, the network arrangement allows firms to concentrate on the parts of the value chain that better reflect their competitive advantage (Link et al., 2002).

Finally, the emergence of a technical community in an industry provides a platform for facilitating exchange of tacit research ideas (Katila and Mang, 2003). It is argued that technical community can facilitate the development of technological competitiveness and economic growth at the nation, state, and city levels (Porter, 1998a; Romanelli and Khessina, 2005). Some governments have been playing a key role in forming such communities. For instance, the Chinese government has been pursuing cluster development for constructing its high-tech industry since the 1990s (Chou et al., 2011).

By engaging in research partnerships, high-tech firms not only draw on partner’s technology pool to develop innovations and in-house capabilities, but also monitor the development of latest technologies and stay alert (Roijakkers and Hagedoorn, 2006). Moreover, R&D collaboration means that high sunk costs for R&D are shared, which are good news especially to young high-tech firms. R&D collaborations enable high-tech firms to realize cost-savings by investing in fewer resources for the same research output. Due to high absorptive capacity, MHT and HT firms can achieve more in terms of productivity gains in relation to research activities (Siliverstovs and Kancs, 2016). This virtuous cycle further increases the likelihood of these firms to engage in future joint R&D activities. Summarizing the above discussion, I propose the following hypothesis:

Hypothesis 1. The propensity to enter research partnership with universities is greater for firms from higher technology sectors.

4.3 Econometric Analysis

4.3.1 Source of Data

The source of data, i.e. PATSTAT, is covered in Chapter 3. The data set employed by this chapter is constructed based on the second data set (mentioned in Chapter 3). The period of study is set to cover between 2001 and 2010, as very few firm observations entered the sample before 2001. The firm-level data set contains 658 Chinese firms who filed joint patents during the period. These data exclude firms that filed joint patents with two or more applicants (implying multiple partnership). The propensity of entering patent collaboration under multiple partnership is subject to the influence of the third applicant, which is beyond the interest of this study.

4.3.2 Measures

4.3.2.1 Dependent variable: the propensity to collaborate with universities

Using the firm-level data set, I explore the likelihood of a firm is going to collaborate with universities on patented technologies. The variable is operationalised as a dummy, which is coded 1 if firm jointly files a patent application with university in a given year, and coded 0 if otherwise. It is expected that firms from higher technology sectors are more likely to collaborate with universities than other firms due to the reasons discussed in section two.

4.3.2.2 Independent variables

The independent variable takes the value 1 if the firm is operating in low-tech sectors, 2 if operating in medium-low technology sectors, 3 if operating in medium-high technology sectors, and 4 if operating in high-tech sectors.

4.3.2.3 Control variables

Firm ownership. Previous studies have suggested that firm ownership has an impact on its R&D activities. In the sample data, there are four types of firms: privately-owned enterprises, state-owned enterprises, foreign-funded enterprises, and ethnic Chinese enterprises[6]. From the descriptive statistics, I found that privately-owned enterprises (POEs) have a strong presence in medium-high and high technology sectors. By contrast, state-owned enterprises (SOEs) have a much weaker presence in these sectors. Boeing et al. (2016) found that POEs obtain higher returns from in-house R&D than SOEs and is the only ownership type that produces and profits from high quality R&D. Yu and Nijkamp (2009) compared the technology

[6] Firms from Hong Kong, Macau, and Taiwan are referred to as ethnic Chinese firms.

catch-up between foreign-funded enterprises and SOEs, and found that SOEs are still lagging behind. To control the effect of firm ownership on the propensity to collaborate with university, I introduce a categorical variable, which indicates the ownership type of a given firm. The base group is foreign-funded enterprises, which includes the wholly-owned foreign firms as well as foreign subsidiaries of multinational enterprises.

Organisational proximity. University spin-offs have emerged as an increasingly important channel of universities to engage in commercialisation activities. These spin-offs, which draws on a lot of resources of university for R&D activities, are no doubt likely to form research partnerships with the parent university. Hence, I introduce a dummy variable to capture the effect of proximity on the propensity to enter research partnership. The dummy variable is coded 1 if a given firm is a spin-off from a university, and 0 if is not.

Multinational background. Multinational enterprises (MNEs) have reportedly established around 1300 R&D facilities in China in 2013 (KPMG, 2013). To tackle the innovation bottleneck of local firms, the Chinese government issued policies that aim at promoting technology advancement via absorbing foreign technologies. Empirical evidence suggests that the presence of MNEs and their inward foreign direct investment positively affect local firms' innovation through knowledge spillovers, such as in forms of technical assistance, and reverse engineering (Liu and Buck, 2007). With respect to the propensity to collaboration with local universities, Zhou (2012) finds that there is a negative relationship between MNEs and university collaborations at host country.

4.3.4 Econometric model

Since the dependent variable of firm-level data set is a binary variable, the logit and probit models are appropriate for estimation purpose. Both models provide similar probabilities, and marginal effects, though they differ in parameter estimates and standard errors. This is because logit and profit models use different functional forms: the former uses the cumulative distribution function of the logistic distribution, while the latter uses the cumulative distribution function of the standard normal distribution. I finally adopt the Probit model as the point of analysis but remain the logit model as a robustness check. The econometric model for H1 is written as follows:

$$Y_{it} = \beta_0 + \beta_x X_{it} + \epsilon_{it}$$

$$Y_{it} = \begin{cases} 1 \text{ if } Y_{it} \geq \alpha_i \\ 0 \text{ if } Y_{it} < \alpha_i \end{cases}$$

Specifically, the outcome Y is a binary variable, which is operationalised as 1 if there is probability, and 0 if there is no probability, X_{it} is a vector of independent variables (including the controls), and α_i is the threshold which the focal firm is considered as operating in a medium-low, medium-high, or high-tech sector.

4.4 Results

Table 4.1 reports summary statistics for the firm-level variables. Table 4.2 provides Spearman's correlation matrix for the firm-level variables. Table 4.3 presents the estimation results of H1. In Table 4.3, Column I presents the effect of all the control variables on the dependent variable; Column II adds the independent variable (i.e. technology sector) to the regression model. There are several findings. First and foremost, the results show that the likelihood of collaborating with universities is higher for medium-high technology firms ($\beta=0.73$, $p<0.01$) than for high technology firms ($\beta=0.59$, $p<0.05$) and for medium-low technology firms ($\beta=0.55$, $p<0.1$). Second, the results show that organizational proximity ($\beta=0.1304$, $p<0.01$) is negatively associated with the propensity to collaborate with universities. Third, it emerges that firm ownership does not play a significant role in affecting firm's decision to collaborate with universities. Lastly, the results reveal that there is a negative association between foreign multinationals and/or their subsidiaries and the propensity to collaborate with Chinese universities.

Table 4. 1 Summary statistics for variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Propensity (1/0)	1,064	.3552632	.478818	0	1
Technology sector	1,064	3.422932	.7937197	1	4
Firm ownership	1,064	2.573308	.9524351	1	4
Organisational proximity (1/0)	1,064	.3449248	.4755673	0	1
Multinational background	1,064	.9332707	.8858999	0	2

Table 4. 2 Spearman's correlation matrix for variables

	(1)	(2)	(3)	(4)	(5)
(1) Propensity	1.0000				
(2) Technology sector	0.0299	1.0000			
(3) Firm ownership	-0.0094	0.0526*	1.0000		
(4) Organisational proximity	-0.4312*	-0.0420	0.0381	1.0000	
(5) Multinational background	-0.2340*	-0.0671*	-0.1789*	0.2349*	1.0000

Table 4. 3 Probit regression results

	I	II
Medium-low technology firms		0.55*
		(0.30)
Medium-high technology firms		0.73***
		(0.26)
High technology firms		0.59**
		(0.26)
SOE	-0.05	-0.00
	(0.21)	(0.22)
POE	-0.12	-0.08
	(0.18)	(0.18)
Ethnic firms	-0.20	-0.17
	(0.17)	(0.17)
Organisational proximity	-1.46***	-1.47***
	(0.11)	(0.11)
Chinese multinational firms	-0.06	-0.08
	(0.14)	(0.14)
Foreign multinational firms	-0.54***	-0.51***
	(0.17)	(0.17)
Year dummies	Included	Included
Constant	0.47	-0.18
	(0.36)	(0.45)
Observations	1,064	1,064

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results of Probit regression suggest that, compared with MLT firms (reference group), the probability of establishing research partnerships with universities is higher for firms from MHT sectors. This finding confirms Hypothesis 1, which states that MHT and HT firms have higher propensity to collaborate with universities. There are three reasons explaining why these firms are engaging in technological collaborations and why they tend to collaborate with universities.

First, because of the rapid rate of technological change in MHT and HT sectors, firms must possess different sets of technologies to compete successfully (Arora and Gambardella, 1990; Wu, 2012). To individual firms, developing broad technologies is both time- and resource-consuming. Under such pressure, collaboration on technologies has increasingly become a common option for firms in the MHT and HT sectors. In addition, firms from these sectors are characterized by high-level absorptive capacity. The higher the absorptive capacity, the more likely that external collaboration will enable firms to realise economies of scale in R&D investment (Wu, 2012), leading to a higher probability to collaborate on technologies.

Second, the learning effects increase especially for MHT and HT firms during technological collaborations (Wu, 2012). Technological collaboration helps these firms gain access to emerging technologies that are not readily available for purchase in markets. In the view of competitive advantage, a firm’s ability to anticipate and respond to new technological trends and market needs is the source of competitive advantage. In this vein, technological collaboration can help firms to quickly identify emerging technologies and seize market opportunities, hence is valued by MHT and HT firms.

Third, in MHT and HT sectors, the innovation success is dependent on technological innovation (Grimpe and Sofka, 2009), which is closely associated with university research (Laursen and Salter, 2006). By contrast, in MLT sectors, the innovation success is relied largely on market inputs, which are typically provided by customers and competitors (Grimpe and Sofka, 2009). This is because the innovations of MLT sectors are not based on cutting-edge scientific knowledge, but rather on adoption and adaptation of general stock of knowledge

(Santamaría et al., 2009). This suggests that firms from different technology sectors have distinctive needs for the level of innovativeness, leading to different strategies on partner selection in technological collaborations.

4.5 Chapter summary

Using a firm-level data set that contains 658 Chinese firms who filed joint patent applications during the period 2001-2010, this chapter explores whether there is a link between the technology sector of firm and the likelihood of collaborating with universities on patent applications.

The research question can be answered positively: the results show that higher industrial sectors are more likely to collaborate with universities for technological innovations. This finding resonates with the finding of Zhou's (2012). To firms from MHT sectors, collaboration on technology is a better option than develop technology on its own, because the former is much more time- and resource-saving than the latter. By collaborating with other firms that have already developed certain technologies, firms are able to realise economies of scale in R&D investment.

With respect to collaborative partners, it is understood that innovation behaviour of the firm plays a role in its partner selection. The innovations of MLT sectors are usually not the result of the latest technological knowledge, but rather the exploitation of existing knowledge (Santamaría et al., 2009). In MLT sectors, creativity is much more important than novelty, and the focus of innovation tends to be associated with process, design, and functionality (Hansen and Serin, 1997). By contrast, novelty is valued highly by firms from the MHT sectors. Technological/scientific knowledge, which is the domain of universities, has been the main platform for innovation. In this vein, it is not difficult to understand that why firms from MLT sector often source knowledge from competitors and customers, while firms from higher technology sectors tend to rely on knowledge from universities (Grimpe and Sofka, 2009).

In practical terms, Chapter 4 has two main implications. First, the finding calls for more government support for firms in medium-low technology sectors to form partnership with universities. For example, government should launch relevant projects aim at promoting collaboration between firms in medium-low technology sectors and universities, and facilitating the innovation capabilities of these firms. Second, universities should consider the ‘innovativeness’ of the co-invention to existing stock of technologies. The focus of research should be improving ‘quality’ instead of ‘quantity’.

Chapter 5 Co-ownership and Joint Patent Quality

5.1 Introduction

China has caught the world's attention by its remarkable GDP growth rate, high-levels of foreign direct investment and export value. Behind the astonishing progress, it is significant advancement in S&T of the country. Based on the successful experiences of the East Asian Tiger economies (i.e. Japan, Taiwan, Korea, and Singapore), the advancement of national economy need to make the strategic shift from imitation to innovation (Kim, 1997). Since patenting activities form the core of a nation's innovation system (Hu and Matthews, 2008), the surge in patenting activities of Chinese firms and organisations since 2001 signals the health of its innovation process. Compared with the East Asian Tigers, China has demonstrated distinctive characteristics of its own in terms of national innovation model (Hu and Matthews, 2008). A major difference is that innovation in China rely largely on universities and universities-run enterprises, whereas in East Asian Tigers national this is relied on public research institutes.

In China, universities are not only a critical source of innovation (Hu and Matthews, 2008) but also a practitioner in forward engineering and spin-offs (Lee, 2005), which are resulted from a series of S&T reforms to the NIS in the early 1980s, when the government drastically cut the funding to universities. Chen and Kennedy (2007) show that universities in Beijing have played an extremely important role in the development of the largest high technology cluster in the country - Zhongguancun. There are beliefs throughout Chinese local authorities that university-developed technologies benefit greatly the economic development, largely owe to the successful experience of Beijing where universities have produced a number of large global companies, such as Lenovo, and Founder. Despite concerns over conflicts between commercialisation, and teaching and research, as well as over university's power on spin-off's operation, Chen and Kennedy (2007) suggest that for China, maintaining a close relationship between universities and industry is considered healthy than harmful. The study of Xue (2005) also suggests that close relationship between universities and university-affiliated enterprises has been making significant contribution towards the development of high-tech industry.

The business sector in China is increasing their presence in international patenting activities since 2001 (Hu and Matthews, 2008; Schaaper, 2009). This can be largely attributed to the spillover effects of FDI to China in the 1990s. Using a panel of Chinese provincial data from 1995-2000, Cheung and Ping (2004) empirically show that FDI during the 1990s has promoted R&D activity by Chinese firms via various channels, such as reverse engineering, labour mobility, demonstration effects, and so on. This helps Chinese firms shorten the process of invention and improves their innovation capability. China, like East Asian Tigers, find itself benefiting from economic activities of developed economies. Based on these evidences, it is argued that collaboration with cross-border partners is likely to be beneficial for enhancing quality of joint patents. Currently, there are no known studies specific to joint patenting in China. The only empirical work that looks at cross-border joint patenting is from Briggs (2015), who employs a large panel of patent data from 135 countries and find that international collaboration strongly increases the value of joint patent.

This chapter aims to fill the literature gap by investigating joint patenting performance in China. It analyses whether co-ownerships with cross-border partners and universities would enhance joint patent quality, measured by forward citations. Answer to this question is critical as not only it will inform policymakers on the development of public policies to encourage collaborative relationships that facilitate ongoing innovation, but also it will provide useful information to firms on which collaborative efforts will most impact innovation performance.

The analysis of this chapter is drawn on a panel of patent data from the European Patent Office covering 5232 joint patent observations for the period 1984-2010. Joint patent quality is measured via forward citations. I calculate the number of forward citations received in five years within the first publication date. In the innovation literature, it has established that a higher number of forward citations corresponds to high patent quality (e.g. Trajtenberg, 1990; Henderson et al., 1998; Hall et al., 2005). Employing a range of different count regression analyses, the analysis examines the probability that a joint patent is high quality resulted from: 1) cross-border co-ownership; 2) university co-ownership; and 3) the presence of organisational proximity between co-owners. In a nutshell, the results suggest that while cross-border co-ownership on its own is a strong predictor of joint patent quality, the positive effect of university co-ownership on quality is clearly observed when interacting with cross-border co-ownership. Furthermore, the results show that joint patent applications unaffected by organisational proximity are more likely to benefit from university co-ownership.

The rest of the chapter is organised as follows. Section two reviews relevant literatures and proposes hypotheses for the study. Section three provides details on the data used. Section four presents the findings. Lastly, the chapter concludes by discussing the findings and summarising main arguments.

5.2 Literature Review

The literature that is specific to joint patenting is scarce. Joint patenting, also known as co-patenting, is the phenomenon that a patent is claimed ownership by more than one organisation. Joint patent may not be a clear indicator of R&D collaboration, which may "result in patents with a single owner or no patent at all" (Briggs, 2015, p.1567); rather, it may combine information on R&D collaboration and IP sharing arrangement (Belderbos et al., 2014).

The literature suggests that the decision to pursue joint ownership of patents rights may be due to a variety of reasons. First, joint patents may be anticipated outputs of formal collaborations between partners (Hicks, 2000). Partners may resort to joint patenting when the innovation under development has the potential to be a core competency for one partner and a risk that is caused by abuse of IP rights by the other partner (Teng, 2007). Second, joint patents may be unanticipated outputs of small scale, informal collaborations between firms (Belderbos et al., 2014; Hagedoorn, 2003) that are difficult to divide the intellectual property between the participants. Third, firms that engaged in joint patenting in the past (Hagedoorn, 2003) or have history of successful alliance (Kim and Song, 2007) are more likely to engage in joint patenting for innovations.

A recent stream of research explores the factors that impact the joint patent quality. Among them, the effect of co-ownership has been successfully identified as a factor that impact on joint patent quality. Analysing a panel of 85706 patent observations from 164 firms in the United States, Europe, and Japan between 1996 and 2003, Belderbos et al. (2014) reported that while both intra-industry and inter-industry co-ownership yield greater forward citations, the effect of university co-ownership is insignificant. Using a panel of 141,920 joint patent observations in 150 countries over 31 years, Briggs (2015) found that while multi-country co-ownership positively impact patent quality (assessed as forward citations) in both the short and long term (three years and over the life of the patent, respectively), university co-ownership is not found to have an immediate impact but it does enhance the patent quality in the long term. Both the studies of Belderbos et al. (2014) and Briggs (2015) enhance the current understanding on the effect of co-ownerships on joint patent quality. Yet, the depth of extant research could reach further.

Dissimilar from previous research, this research not only explores the factors that account for heterogeneity in patent quality in an important emerging country – China, but also improves the econometric analysis in extant research. The analysis looks at 5233 joint patents in China between 1985 and 2010. The likelihood that a joint patent is categorised as “high quality” is modelled to depend on three key independent variables: 1) the presence of international partners; 2) the presence of university partners; and 3) the presence of organisational proximity between partners.

5.2.1 Cross-border co-ownership

Cross-border patent ownership signals international collaboration in patenting activities, which mainly happened in developed countries, now have observed consistent growth in emerging economies (Guan and Chen, 2012). International collaboration is believed to serve an important channel for international knowledge diffusion, enabling the flow of knowledge, technology, and skills from one country to the other one (Guan and Chen, 2012). Moreover, it provides a platform for firms to expand their knowledge base, in particular for those pursuing higher level innovations (Hewitt-Dundas, 2006; Gilsing et al., 2008; Tether, 2002). Zheng et al. (2012) noted that international collaboration in patenting is necessary in encouraging economic development and enhancing national competitiveness. Guan and Chen (2012) suggested that wide and deep international knowledge participation can help emerging countries with their technology catch-up greatly. At the firm-level, the literature provides a variety of reasons as to why collaborations with international partners lead to higher quality innovations. First, firms that collaborate with international partners have access to information that may not be available in the home country, thereby in a better position to achieve more novel product/service innovation than those who do not. Second, interactions between partners located in different stages of development can generate unique combinations of resources and knowledge that lead to novel creations (Briggs, 2015).

5.2.2 University co-ownership

Universities are believed to be the origins of scientific knowledge, where basic and applied research are their strengths (Hemmert, 2004; Perkmann et al., 2013). Baba et al. (2009) noted that in industries where university collaboration is the dominant source of knowledge, firms that choose not to collaborate with universities may fall behind. However, the influence of co-ownership with universities on joint patent quality is both theoretically and empirically ambiguous in the wake of two opposing schools of thought.

The first school of thought underlines a variety of benefits collaborate with the academia. First, university collaboration can help lower firms' search costs since universities have experienced faculty staff, established research facilities, and strong track record of publishing scientific findings in certain areas such as chemistry and biology. Second, there are less disputes over co-developed knowledge created during university-firm collaborations, because "the business of universities is not to compete with companies but to 'educating people, developing their faculty and doing basic research" (Belderbos, 2014, pp. 843). Third, firms' problem-solving skills and the ability to search and integrate external knowledge can be enhanced via close interactions with universities. The interactive learning enables firms to not only capture the skills of learning and tacit knowledge of the field, but also to understand the mind-set of university inventors so as to allocate right resources and adjust strategies to foster the collaboration. In the Chinese context, the pro-university school is represented by Chen and Kenney (2007) and Hu and Matthews (2008), who suggest that universities in China have been making great contribution to the country's economic development.

An opposing school of thought suggests that collaboration with universities do not result in satisfactory performance. Funk (2013) suggested that joint patent quality is sensitive to ownership relations. Lhuillery and Pfister (2009) found that firms conducting research with universities are more likely to face delay or even 'cooperation failure' than with suppliers or customers due to the divided opinions in managing deadlines, technological distance, and intellectual property rights. Using French innovation data, Monjon and Waelbroeck (2003) found a negative relationship between collaborations with universities and product innovation performance.

5.2.3 The Presence of Organisational Proximity

The role of organisational proximity has been widely discussed in the literature on inter-organisational collaboration (e.g. Knoben and Oerlemans, 2006) and innovation (e.g. Capaldo and Petruzzelli, 2014). The concept has been defined in slightly different ways. Example of a narrow definition is by Oerlemans and Meeus (2005), who define organisational proximity as "actors that belong to the same space of relations". A broader definition is given by Torre and Rallet (2005), as "actors whose interactions are facilitated by rules and routines of behaviour and that share a same system of representations, or set of beliefs". In this chapter, the definition of organisational proximity is defined as actors that belong to the same parent organisation.

Theoretically, the seminal work of Boschma (2005) argues that while a moderate level of organisational proximity is beneficial for learning and innovation, too much organisational proximity leads to the opposite. Empirically, Broekel and Boschma (2011) show that while organisational proximity was important driver of alliance formation, it does not lead to superior innovation performance. Cassi and Plunket (2013) find similar empirical evidence that organisational proximity was not conductive to innovative performance of firms. Analysing a sample of 1515 R&D alliances, Capaldo and Petruzzelli (2014) show that both geographic distance and organisational proximity negatively affect the innovative performance of the alliances. However, the two characteristics positively affect the innovative performance of alliances when jointly considered, showing that the two characteristics are contingent upon one another.

The literature on proximity and innovation in China is scarce. A study of Liang and Zhu (2002) is among the few existing studies show that geographical proximity (distance) is an important facilitator (barrier) of inter-regional research collaboration in China. Analysing a panel of Chinese patent data from 1985 to 2004, Hong and Su (2013) show that although geographical distance is obstructive in achieving university-industry collaborations, it can be bridged by institutional proximity between partners. In all, the role of organisational proximity is under-studied in the literature specific to joint patenting.

5.3 Data

5.3.1 Source of Data

The source of data for this chapter is covered in Chapter 3. The data set for this chapter includes 5328 joint patents representing the number of partnerships between 784 focal firms and partners during period 1985-2010. Joint patents developed by three or more applicants are excluded from the sample, as multiple partnerships can make interpretation complex. Figure 4.1 shows that both the number of joint patents and the number of joint patents with university co-ownership and cross-border co-ownership have been growing consistently.

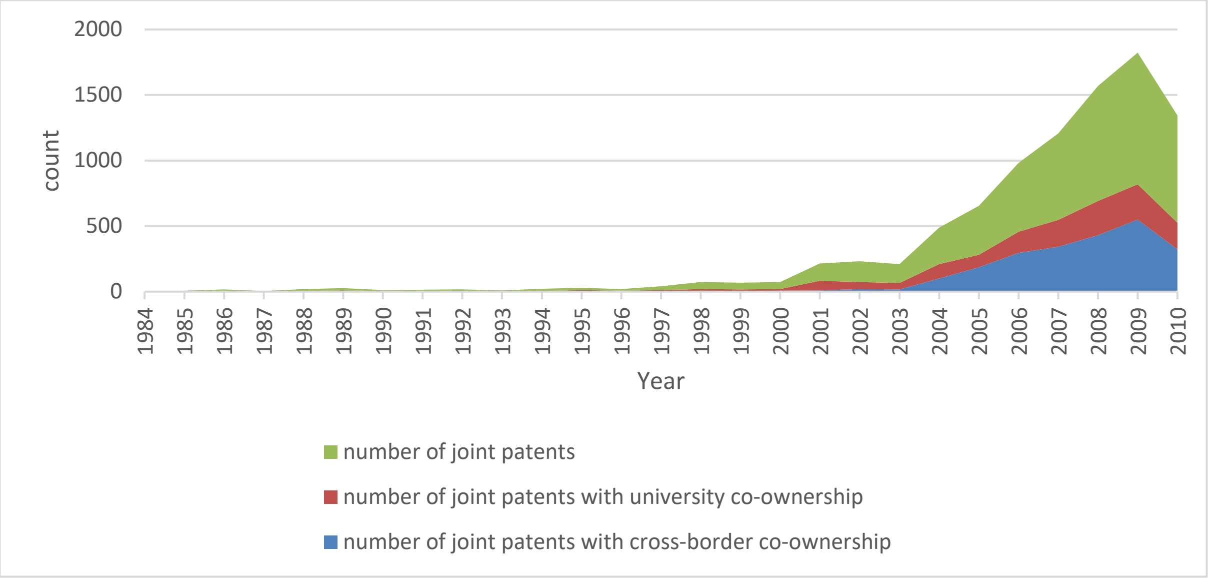

Figure 5. 1 Trends in joint patenting and co-ownerships

5.3.2 Measures

This section discusses the variables including dependent variable, independent variables, and control variables. Table 5.1 gives definition of variables and presents summary statistics.

Table 5. 1 Definition of variables and summary statistics

Variable	Definition	Obs	Mean	Std. Dev.	Min	Max
Cross Border	Cross-border co-ownership (1/0)	5,277	0.44002	0.49644	0	1
University	University co-ownership (1/0)	5,293	0.29568	0.45639	0	1
Organisational proximity	Partners belong to the same parent organisation (1/0)	5,328	0.58615	0.49257	0	1
Forward	Number of forward citations received within five years of first publishing	5,293	2.99641	7.69207	0	193
Backward	Number of patent references cited by a given invention	5,293	5.02078	6.33774	0	107
NPL citations	Number of scientific literature cited by a given invention	5,293	0.59135	3.00255	0	107
Inventors	Number of inventors worked for a given invention	5,293	4.56679	3.18074	0	24
Patent families	A collection of patent applications taken in various countries to protect a single invention	5,293	4.32477	3.65864	1	32
Claims	Number of claims in the patent application	5,293	4.43132	8.09256	0	110
Technologies	Number of technology fields a given invention involved	5,293	1.54317	0.75535	0	7
WIPO	Patent field dummies	5,233	3.12039	1.08314	1	5

5.3.2.1 Dependent variable

Joint patent quality. I use forward citations to proxy the quality of joint patents. The variable is widely used in innovation literature for a variety of purposes, including measuring firm innovative performance (Sampson, 2007, Singh, 2008), innovation impact (Miller et al., 2007), and innovation output (Singh, 2008). Trajtenberg (1990) found that forward citations are positively and significantly correlated with independent measure of returns from innovation. Hall et al. (2005) found that compared to those less frequently cited, patents with high citations are more likely to be profited from economic activities. To control for time truncation effect in the dependent variable, I use a five-year time window to observe the effect of the explanatory variables of interests (i.e. cross-border and university co-ownerships) on the dependent variable.

5.3.2.2 Independent variables

There are three explanatory variables considered to impact joint patent quality: 1) the presence of cross-border co-ownership; and 2) the presence of university co-ownership, and 3) the presence of organisational proximity. The first independent variable of interest is whether the co-owners originated from countries other than China. I construct a dummy variable that takes the value 1 if there is the joint patent is owned by firms in more than one country, and takes the value 0 if otherwise. Of the 5233 joint patent observations in the sample, 44% have at least one collaborator that is originated from other countries. As discussed in the literature, cross-border co-ownership is believed to expand firm’s knowledge base, thereby cross-border co-ownership is expected to have a positive and significant impact on joint patent quality.

The presence of a university co-owner is included as an explanatory variable in the empirical estimation. University partner is identified by the patent data via the variable ‘sector’. A dummy variable is constructed taking the value 1 if the joint patent is owned by a university partner, and 0 if otherwise. Of the 5233 joint patent observations in the sample, 29.57% have at least one collaborator that is from a university. Given the two opposing schools of thought, the expected sign of university co-ownership is theoretically ambiguous.

The control variables for this chapter include number of technologies, number of inventors, number of backward citations, number of NPL citations, number of claims, and WIPO patent dummies. These are covered in Chapter 3.

Table 5.2 presents the correlation matrix of all variables. I conducted a test for multicollinearity among variables (Appendix 1). The mean test statistics, i.e. variance inflation factor (VIF) returns 3.31. As a rule of thumb, multicollinearity becomes a problem when VIF exceeds 10 and above. Clearly, multicollinearity is not a severe issue in this study.

Table 5. 2 Correlation matrix for all variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Forward citations	1										
(2) Organisational proximity	0.1217*	1									
(3) Cross Border collaboration	0.2966*	0.3455*	1								
(4) University collaboration	-0.0645*	-0.7125*	-0.3712*	1							
(5) Backward citations	0.3346*	0.1688*	0.2375*	-0.1049*	1						
(6) NPL citations	-0.0141	-0.2621*	-0.1662*	0.2229*	0.0607*	1					
(7) Inventors	-0.1216*	-0.2423*	-0.4439*	0.2874*	-0.0859*	0.1052*	1				
(8) Patent families	-0.1731*	-0.2440*	-0.3496*	0.2053*	-0.2654*	0.1101*	0.3368*	1			
(9) Claims	0.3805*	0.1545*	0.1535*	-0.0955*	0.3395*	0.0897*	-0.0534*	-0.0738*	1		
(10) Technologies	0.1295*	-0.0518*	-0.1007*	0.0709*	0.0295*	0.1142*	0.0545*	0.1597*	0.1584*	1	
(11) WIPO	-0.1946*	-0.1903*	-0.4098*	0.1526*	-0.1830*	0.1878*	0.2418*	0.3097*	-0.1318*	0.1519*	1

5.3.3 Econometric analysis

5.3.3.1 The model

The econometric model is specified as follows:

$$Citations_i = \beta_0 + \beta_1 CrossBorder_i + \beta_2 University_i + + \beta_3 OrgProx_i + \beta_3 Technologies_i + \beta_4 Inventors_i + \beta_5 Backward_i + \beta_6 NPL_i + \beta_7 WIPO_i + \beta_8 Claims + \epsilon_i$$

where $Citations_i$ denotes the number of forward citations received within five years of patent publication; $Cross\text{-}border_i$ indicates the presence of cross-border co-ownership. $University_i$ denotes the presence of university co-ownership. $Technologies_i$ represents the number of technology fields captured by the patent. $Inventors_i$ refers to the number of inventors worked for a given invention. $Backward_i$ denotes the number of patent literature cited by a given invention. NPL_i refers to the number of scientific literature included in a given patent application. $WIPO_i$ is a dummy variable that indicates the type of patent classified by the WIPO. $Claims_i$ defines the scope of the protection sought in a patent application.

5.3.3.2 Econometric method

Econometric models for count data are covered in Chapter 3. In this chapter, PQGPMLE is employed as the benchmark model; NB1 as the main model; and results of NB2 are used for arobustness checks.

5.4 Results

This section firstly presents the benchmark results (PQGPMLE) before discusses the main results (NB1), then concludes by reporting the robustness test (NB2).

5.4.1 Benchmark results

Table 5.3 reports the benchmark results (marginal effects) for the Poisson quasi-generalized pseudo-maximum likelihood estimator with robust standard errors (i.e. PQGPMLE). Appendix 4 reports the benchmark results (model effects) for PQGPMLE.

As robustly shown across all columns of Table 5.3, university co-ownership has a positive and statistically significant impact ($p<0.01$) on forward citations received, other factors being constant.

As shown in Table 5.3, the effect of organisational proximity on forward citations is negative and weakly significant ($p<0.1$) in Column IV, whereas the effect changed to be negative and statistically significant ($p<0.01$) in Column VI. In practical terms, this means that, organisational proximity can lower joint patent value by decreasing 1 forward citations, controlling for other variables. Column VIII (i.e., the full model) shows that organisational proximity is uncorrelated to forward citations.

As indicated by Column II, V, VI, and VIII, the effect of cross-border co-ownership on joint patent quality is positively and statistically significant ($p<0.01$). In practical terms, the coefficients suggest that international patent collaboration increases forward citation by 3.7 to 4 units, other factors being constant.

Table 5. 3 Benchmark results of PQGPMLE

	I	II	III	IV	V	VI	VII	VIII	VIIII
	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE	PQGPMLE
Cross-border		3.653***			3.899***	3.955***		3.891***	2.859***
		(0.404)			(0.463)	(0.497)		(0.470)	(0.380)
University			1.240***		1.659***		1.604**	1.695***	0.490
			(0.470)		(0.444)		(0.641)	(0.600)	(0.516)
Cross-border*University									4.044***
									(1.180)
Organisational proximity				-0.664*		-1.090***	0.413	0.040	0.285
				(0.372)		(0.374)	(0.411)	(0.423)	(0.392)
Backward citation	3.748***	3.235***	3.787***	3.891***	3.267***	3.447***	3.705***	3.260***	3.117***
	(0.359)	(0.243)	(0.378)	(0.421)	(0.253)	(0.305)	(0.364)	(0.266)	(0.232)
NPL citation	0.255	0.216	0.057	0.118	-0.022	0.001	0.094	-0.019	-0.044
	(0.346)	(0.275)	(0.328)	(0.348)	(0.268)	(0.283)	(0.328)	(0.269)	(0.255)
Inventors	-0.122**	0.113**	-0.144**	-0.136**	0.092*	0.108**	-0.141**	0.092*	0.096**
	(0.056)	(0.050)	(0.058)	(0.060)	(0.049)	(0.052)	(0.057)	(0.049)	(0.048)
Patent family size	-0.350***	-0.185***	-0.360***	-0.365***	-0.189***	-0.201***	-0.352***	-0.188***	-0.176***
	(0.066)	(0.044)	(0.068)	(0.071)	(0.045)	(0.047)	(0.067)	(0.046)	(0.045)
Patent claim	0.320***	0.279***	0.326***	0.334***	0.285***	0.300***	0.318***	0.284***	0.271***
	(0.047)	(0.033)	(0.049)	(0.053)	(0.035)	(0.040)	(0.047)	(0.035)	(0.031)
Technology field	0.674***	0.529***	0.643***	0.677***	0.489***	0.528***	0.633***	0.488***	0.487***
	(0.191)	(0.146)	(0.182)	(0.193)	(0.137)	(0.148)	(0.178)	(0.138)	(0.127)
Chemical patent	1.970***	1.172**	1.949***	2.091***	1.050**	1.283**	1.863***	1.043**	1.151**
	(0.551)	(0.477)	(0.588)	(0.588)	(0.516)	(0.513)	(0.579)	(0.519)	(0.493)
mechanical engineering patent	0.832	0.875	0.356	0.680	0.258	0.648	0.326	0.254	0.418
	(0.627)	(0.593)	(0.630)	(0.635)	(0.587)	(0.604)	(0.623)	(0.588)	(0.574)
electrical engineering patent	0.049	0.808	-0.218	-0.054	0.538	0.737	-0.224	0.535	0.134
	(0.592)	(0.563)	(0.604)	(0.601)	(0.577)	(0.585)	(0.598)	(0.578)	(0.529)
Instrument patent	-0.619	-0.595	-0.755	-0.663	-0.768	-0.652	-0.762	-0.769	-0.733
	(0.567)	(0.509)	(0.606)	(0.593)	(0.547)	(0.543)	(0.599)	(0.547)	(0.521)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Specifically, university co-ownership is found to benefit joint patent quality by increasing between 1.2 to 1.7 forward citations. The increase in forward citations may be seemingly small, yet Hall et al. (2005), Harhodd et al. (1999), and Trajtenberg (1990) have empirically shown that forward citation is a strong indicator of economic value of the innovation or the firm. My result supports the finding of Furman and Stern (2011) that university patenting has a positive and statistically significant impact on innovative performance.

The result is opposite of that of Briggs (2015), who finds that university co-ownership does not have a statistically significant impact on forward citations received within three years. Possible explanations for the opposite results include different estimation strategy and time frame of the dependent variable. In her studies, Briggs (2015) employs the Logit regression estimate the likelihood of a joint patent is high quality (using a threshold to determine if a joint patent is high quality). Whereas in this study, I employ Poisson regression to estimate the effect of explanatory variables (i.e. cross-border and university co-ownerships) on joint patent quality (using forward citations received within five years). In empirical estimation, Logit regression is used to fit dichotomous data, which means dependent variable takes one of only two possible values representing failure or success. Poisson regression is used to fit count data, which takes positive numbers, and each represents an independent event.

Furthermore, Briggs (2015) reports an insignificant effect of university co-ownership in the short term (using forward citations receive within three years), and a positive and statistically significant effect of university co-ownership in the long term (citations received since joint patent made public). In this research, I look at forward citations receive within five years, which is a longer time frame than that of Briggs (2015).

As indicated by columns II and V, cross-border co-ownership is positive and statistically associated with forward citations. In practical terms, the coefficients suggest that international patent collaboration increases forward citation by 3.7 to 3.9 units. This result supports the findings of extant research on country and firm level.

At the country level, Guan and Chen (2012) suggest that international collaboration in patenting activities plays a significant role in helping emerging countries to catch up with developed ones. Such collaborations serve an important mechanism that enables the diffusion of knowledge, technology, and skills from one country to the other country; for the emerging countries, such collaborations are necessary in encouraging technological development and enhancing national competitiveness (Zheng et al., 2012).

At the firm-level, findings of Gilsing et al. (2008), Hewitt-Dundas (2006), and Tether (2002) suggest that cross-border collaboration allows firms to expand their knowledge base and enhance innovation performance in the long run. Since all the cross-border partners are originated from developed countries, this suggests that international patenting collaboration can enhance further the invention quality of Chinese firms. The studies of Hu and Matthews (2008), Guan and Chen (2012), and Briggs (2015) have suggested that interactions between partners with substantial development gap can generate unique combinations of resources and knowledge.

The coefficient of interaction between cross-border collaboration and university collaboration is statistically significant and positive. The result shown in Column VIIII indicates that this can increase 4 more citations. The finding confirms the significance of partial effect for the subgroup of university collaboration.

In terms of the control variables, Table 5.3 shows that the signs of control variables are largely constant across all models. Specifically, Column I to VIII shows that backward citations have a positive and statistically impact on forward citations. The result shows that every backward citation listed on the patent application leads to the increase in forward citations between 3.3 to 3.9 units. This positive effect is the second largest found in the regression – the first is cross-border co-ownership.

Table 5.3 shows that the relationship between the size of invention team and forward citations is unclear. While Column I, III, IV, and VII show negative and significant effects, Column II, V, VI, and VIII show positive and significant effects on forward citations.

The effects of the size of patent family are consistent across all Columns in Table 5.3. The coefficients suggest that a unit increase in patent family leads to decrease in forward citations between 0.2 to 0.4 units.

Column I to VIII indicates that the number of patent claims listed on a joint patent is positively associated with forward citations received. Specifically, one additional patent claim would increase forward citations by 0.3 unit.

Column I to VIII indicates that the number of technology fields listed on a joint patent positively impacts on forward citations received. Specifically, one additional technology field can increase forward citations between 0.5 and 0.7 units.

5.4.2 Main results and discussion

The main results for the Negative Binomial regression model with linear variance function (i.e. NB1), are reported in Table 5.4. For the independent variables, a consistent result is that cross-border co-ownership has a strong positive effect on joint patent quality (as captured by forward citations received).

Table 5. 4 Main results of NB1

	I	II	III	IV	V	VI	VII	VIII	VIIII
	NB1	NB1	NB1	NB1	NB1	NB1	NB1	NB1	NB1
Cross-border		2.131***			2.278***	2.097***		2.332***	1.800***
		(0.187)			(0.199)	(0.202)		(0.193)	(0.186)
University			-0.221		0.617***		0.673*	1.763***	0.792*
			(0.168)		(0.217)		(0.371)	(0.509)	(0.416)
Cross-border*University									2.444***
									(0.602)
Organisational proximity				0.647***		0.219	0.998***	1.035***	1.114***
				(0.156)		(0.203)	(0.258)	(0.296)	(0.296)
Backward citation	2.186***	2.009***	2.171***	2.127***	2.028***	1.995***	2.134***	1.998***	1.992***
	(0.099)	(0.101)	(0.100)	(0.098)	(0.103)	(0.102)	(0.098)	(0.098)	(0.095)
NPL citation	-0.095	-0.020	-0.064	0.030	-0.090	0.020	0.015	-0.010	-0.004
	(0.119)	(0.134)	(0.122)	(0.117)	(0.135)	(0.134)	(0.117)	(0.126)	(0.128)
Inventors	-0.062**	0.053**	-0.055**	-0.041	0.044	0.058**	-0.047*	0.052**	0.040
	(0.025)	(0.026)	(0.025)	(0.025)	(0.027)	(0.026)	(0.025)	(0.026)	(0.027)
Patent family size	-0.214***	-0.139***	-0.208***	-0.195***	-0.147***	-0.134***	-0.202***	-0.135***	-0.131***
	(0.032)	(0.030)	(0.033)	(0.031)	(0.031)	(0.029)	(0.032)	(0.030)	(0.029)
Patent claim	0.110***	0.107***	0.110***	0.110***	0.108***	0.107***	0.111***	0.111***	0.112***
	(0.014)	(0.016)	(0.014)	(0.013)	(0.015)	(0.015)	(0.012)	(0.013)	(0.013)
Technology field	0.574***	0.570***	0.574***	0.566***	0.571***	0.569***	0.560***	0.559***	0.606***
	(0.091)	(0.099)	(0.092)	(0.088)	(0.098)	(0.097)	(0.086)	(0.090)	(0.090)
Chemical patent	1.301***	0.813**	1.324***	1.208***	0.747**	0.776**	1.100***	0.481	0.571
	(0.339)	(0.329)	(0.336)	(0.347)	(0.339)	(0.333)	(0.368)	(0.366)	(0.374)
mechanical engineering patent	0.130	0.007	0.190	0.148	-0.134	0.002	0.001	-0.355	-0.290
	(0.364)	(0.356)	(0.364)	(0.374)	(0.364)	(0.358)	(0.392)	(0.387)	(0.396)
electrical engineering patent	-0.407	-0.022	-0.387	-0.483	-0.048	-0.052	-0.571	-0.209	-0.358
	(0.338)	(0.346)	(0.336)	(0.347)	(0.355)	(0.351)	(0.363)	(0.378)	(0.382)
Instrument patent	-0.593	-0.594*	-0.567	-0.652*	-0.654*	-0.621*	-0.753*	-0.868**	-0.857**
	(0.367)	(0.358)	(0.362)	(0.372)	(0.368)	(0.359)	(0.386)	(0.388)	(0.394)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As indicated by Columns II, V, VI, VIII, and VIIII, the coefficient of cross-border co-ownership is statistically significant and positive ($p<0.01$). The variable is found to benefit joint patent quality by increasing between 1.8 to 2.3 forward citations. This finding is in line with previous findings of Briggs (2015), and it resonates with the finding of Beers et al. (2014), Hewitt-Dundas (2006), and De Jong and Freel (2010). The internationalisation of joint patenting activities provides firms the access to country-specific resources, such as tacit knowledge of a certain technological field. Such knowledge may be in short supply in firms' home country, therefore the access to such knowledge is crucial to generate valuable inventions.

As a robustness check, the analysis further distinguishes between intra-firm cross border co-patenting and inter-firm cross border co-patenting. The results are reported in Appendix 5. The results show that while both types of cross border co-patenting are conducive to high joint patent performance, inter-firm cross border patenting, on average, brings 0.1 more citation. The finding provides further evidence that internationalisation of joint patenting activities is linked to valuable inventions.

As shown in Column III, the coefficient of university co-ownership is insignificant although negative. However, the coefficient of the variable changes to be positive and statistically significant when cross-border co-ownership is added to the regression, as indicated in Column V. The coefficient also shows positive but weak significance when the organisational proximity variable is added, as demonstrated in Column VII. In the full model (Column VIIII), all the independent variables are positive and statistically significant. This finding is important as it suggests that international university collaboration may help Chinese firms to achieve higher innovation capabilities. This finding also links to that of Ponds et al. (2009) that university knowledge spillovers resulting from research collaboration can occur over longer geographical distances. Overall, university co-ownership can benefit joint patent quality by increasing 0.6 - 1.8 forward citations.

The coefficient of interaction between cross-border collaboration and university collaboration is statistically significant and positive. The result is shown in Column VIIII. It is found to increase 2.4 more citations. The finding confirms the significance of partial effect for the subgroup of university collaboration.

In general, organisational proximity has a positive and statistically significant effect ($p<0.01$) on forward citation, as indicated robustly in Column IV, VII, and VIII. Organisational proximity between partners is found to increase 0.2 – 1 forward citation. The positive effect of organisationl proximity appears to be opposed to those formulated in Chapter 4. However, it should be noted that two chapters address different research questions using different levels of data set. While Chapter 4 investigates the propensity of co-patenting at the firm-level, this chapter examines the effect of co-ownerships on joint patent performance at the patent-level.

The coefficient of organisational proximity becomes statistically insignificant although positive, when cross-border co-ownership is added (Column VI). This is interesting result, as it suggests that collaboration between units of the same multinational firms is not conductive to higher quality joint patent. The finding is consistent with that of Cassi and Plunket (2013), who find that organisational proximity, along with geographical proximity, are important determinants of network formation. However, once network ties are established, the role of organisational and geographical proximities will be substituted by social proximity, therefore both organisational and geographical proximities become less relevant to the future innovative performance of firms.

As far as the control variables are concerned, the findings are consistent with the benchmark results reported in Table 5.3. Specifically, an additional backward citation leads to 2 - 2.2 more forward citations. Since research has suggested that forward citation is strongly correlated with economic value, this effect is significant in economic terms. It could be that inventions that cite many prior patent applications are developed from important existing inventions that are commercially profitable compared to those stemmed from basic research and cite few prior patent applications. The insignificant effect of non-patent literature, which refers to scientific literature listed on joint patent application, to some extent reinforces the previous argument.

A unit increase in patent family size reduces forward citations by 0.1 - 0.2, can likely be attributed to two reasons. First, patents granted earlier, which are likely to be greater in family size, may be less valuable due to weaker technological capability of firms at earlier stage. Second, technology life cycle may reach to a mature stage as firms expand patent protection. At this stage, more firms have gained access to the technology and started to invent around. This may explain the decrease in the economic value of joint patent with big family size. Compared with the benchmark results, the reduction in forward citation is smaller.

A unit increase in the number of patent claims increases forward citation by 0.1. This result is consistent with those reported by benchmark results, but the effect on reduction in forward citation is much smaller (0.3 in benchmark results).

A unit increase in the number of technology fields increases forward citation by 0.6. The result is in line with those reported by benchmark results.

To summarise, the consistent outcome is cross-border co-ownership is strongly correlated to joint patent quality (using forward citations). The positive effect of university co-ownership is most significant when interacts with cross-border co-ownership, then with organisational proximity. The effect of organisational proximity is generally positive and statistically significant, except when cross-border co-ownership variable is included and shows an insignificant effect. As far as the control variables are concerned, the results are consistent with those reported by benchmark results in Table 5.3.

5.4.3 Robustness test

I further compare the main results with those estimated by the Negative Binomial regression model with quadratic variance function (NB2). The results are presented in Table 5.5.

Table 5. 5 Robustness test by NB2

	I	II	III	IV	V	VI	VII	VIII	VIIII
	NB2	NB2	NB2	NB2	NB2	NB2	NB2	NB2	NB2
Cross-border		3.768***			3.996***	4.071***		4.001***	3.005***
		(0.451)			(0.512)	(0.553)		(0.524)	(0.434)
University			1.106**		1.542***		1.288**	1.523**	0.443
			(0.480)		(0.455)		(0.644)	(0.607)	(0.538)
Cross-border*University									3.968***
									(1.225)
Organisational proximity				-0.653*		-1.030***	0.226	-0.023	0.212
				(0.395)		(0.387)	(0.459)	(0.449)	(0.418)
Backward citation	4.192***	3.523***	4.197***	4.344***	3.531***	3.739***	4.143***	3.536***	3.370***
	(0.464)	(0.298)	(0.471)	(0.531)	(0.303)	(0.366)	(0.465)	(0.320)	(0.278)
NPL citation	0.330	0.275	0.167	0.201	0.065	0.078	0.188	0.062	0.031
	(0.363)	(0.292)	(0.350)	(0.369)	(0.287)	(0.304)	(0.352)	(0.290)	(0.275)
Inventors	-0.128**	0.111**	-0.146**	-0.141**	0.092*	0.108*	-0.144**	0.092*	0.097*
	(0.060)	(0.053)	(0.061)	(0.063)	(0.052)	(0.055)	(0.061)	(0.053)	(0.051)
Patent family size	-0.328***	-0.184***	-0.335***	-0.343***	-0.188***	-0.199***	-0.330***	-0.188***	-0.174***
	(0.067)	(0.046)	(0.069)	(0.073)	(0.047)	(0.050)	(0.069)	(0.048)	(0.046)
Patent claim	0.353***	0.304***	0.355***	0.367***	0.307***	0.324***	0.350***	0.308***	0.292***
	(0.056)	(0.039)	(0.058)	(0.063)	(0.040)	(0.047)	(0.056)	(0.042)	(0.037)
Technology field	0.653***	0.511***	0.621***	0.653***	0.472***	0.507***	0.616***	0.473***	0.468***
	(0.204)	(0.156)	(0.195)	(0.206)	(0.148)	(0.158)	(0.193)	(0.149)	(0.137)
Chemical patent	2.228***	1.297**	2.207***	2.366***	1.168**	1.408**	2.153***	1.172**	1.268**
	(0.640)	(0.530)	(0.672)	(0.681)	(0.567)	(0.569)	(0.666)	(0.572)	(0.538)
mechanical engineering patent	0.959	1.017	0.493	0.800	0.382	0.780	0.476	0.384	0.540
	(0.714)	(0.659)	(0.709)	(0.720)	(0.647)	(0.670)	(0.706)	(0.650)	(0.629)
electrical engineering patent	0.092	0.875	-0.152	-0.010	0.622	0.813	-0.155	0.624	0.245
	(0.658)	(0.611)	(0.669)	(0.668)	(0.628)	(0.638)	(0.666)	(0.631)	(0.578)
Instrument patent	-0.621	-0.601	-0.751	-0.666	-0.780	-0.667	-0.756	-0.779	-0.737
	(0.637)	(0.557)	(0.671)	(0.663)	(0.595)	(0.594)	(0.667)	(0.596)	(0.562)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Here, the consistent outcome is cross-border co-ownership attracts greater number of forward citations. The positive effect of university co-ownership is confirmed in Columns III, V, VII, and VIII. The interaction term between cross-border collaboration and university collaboration remains statistically significant and positive, as shown in Column VIIII. However, organisational proximity is found to be negatively related to forward citations when cross-border co-ownership is added, as shown in Columns VI. To summarise, the robustness test firmly supports the role of cross-border co-ownership in enhancing joint patent quality.

To summarise, the robustness test firmly supports the role of cross-border co-ownership in enhancing joint patent quality (using forward citations). As far as the control variables are concerned, the robustness test shows that the effects of all the control variables are consistent with the benchmark and main results.

5.5 Chapter summary

The literature that specifically address joint patenting is relatively scarce, compared with the literature on research and development collaboration. It is understood that not all the collaborative activities lead to publication of research output. This is the case for joint patenting – it is possible that research collaborations between organisations could end up with a single patent owner or none. Nevertheless, a successful joint patent can convey important innovation of a collaborative relationship. It is important for both firm manager and policymakers to recognize the growing importance of joint patenting in patenting activity, and to understand how joint patenting can facilitate novel innovations. Using forward citations as the measure of joint patent quality, this chapter explores how cross-border and university co-ownerships, as well as organisational proximity impact joint patent quality for an emerging country - China.

There are three main findings. First, cross-border ownership positively impacts on quality of joint patents. The results are consistent in benchmark and main results, as well as in robust checks. My empirical evidence demonstrates that cross-border co-ownership is found to benefit joint patent quality by increasing between 2 to 2.3 forward citations. My finding is consistent with previous findings of Briggs (2015), and it agrees with the result of Beers et al. (2014) that the geographical diversity of partners positively influences innovation performance of firms (using sales of incremental products per employee). My finding can be explained from existing empirical findings on country and firm level. At the country level, emerging countries such as China, can benefit greatly from international patent collaboration, which allows them to learn from the experience of industrialisation from the developed countries and to catch up in S&T (Hu and Matthews, 2008). At the firm level, international collaboration can help Chinese firms expand their knowledge base and innovation performance via interaction with the developed country firms.

As a robustness check, the analysis further analyses the difference between the effects of intra-firm cross border co-patenting and inter-firm cross border co-patenting on patent value. The results show that the latter is linked to more valuable inventions (as measured by forward citations received) than the former.

Second, the main results show that university co-ownership alone has an insignificant effect on joint patent quality. Yet, when cross-border co-ownership is added, university co-ownership becomes positive and statistically significant. This is an important finding, as it implies that international university collaboration has successfully produced high quality inventions. This can be explained by university knowledge spillovers resulting from research collaboration can occur over longer geographical distances (Ponds et al., 2009). Collaboration between academic institutions and organisations residing in different countries is likely to produce high quality joint patents because university knowledge spillovers are not geographically confined. Public policies that encourage joint patenting with foreign academic institutions should be explored.

Third, positive effect of organisational proximity is observed and strong in the base and full model. The positive effect is weak when the university co-ownership variable is controlled for. The positive effect ceases when the cross-border co-ownership variable is added. This result suggests that collaboration between different subsidiaries of a multinational firm/subsidiary and parent firm is not conducive to high joint patenting performance. Given that joint patenting activities in China are dominated by those of multinational firms, this result raise the question whether these innovation activities are value-added, or they have reached to a mature stage hence their joint patents are less valuable.

Chapter four has two implications. First, since the results show that collaboration between partners from different countries can generate novel inventions, public policies that encourage cross-border joint patenting with foreign countries should be explored. Second, since the results show that international university collaboration has an insignificant effect on joint patent quality, policy makers should explore how to align university research with industrial innovations.

Chapter four has not investigated the impact of firm-level characteristics on joint patent performance, due to the lack of accessing to firm-level financial data. It would be fruitful to explore how firm characteristics influence joint patent performance, by matching firm-level data with patent level data. For example, possible research questions could be: 1) What are the firm-level determinants of joint patent performance? 2) Does R&D expenditure of the firm affect joint patent performance?

Chapter 6 The Effects of Co-ownerships on Joint Patent Quality Re-examined – Evidence from 80 countries

6.1 Introduction

Innovation activities have become increasingly open for acquiring tacit knowledge and diverse skills, and sustaining competitiveness. Among the sources of knowledge and capabilities, universities and international partners stand out as impactful ones, especially in R&D intensive industries (Natalicchio et al., 2017).

The endogenous growth models identify international knowledge spillovers as a key driver of catching up and income growth for the developing countries (Fagerberg, 1994; Grossman and Helpman, 1991). Among the channels of knowledge spillovers, cross-border R&D collaboration is identified as a major one. The logic behind that is such collaboration provides a platform for firms to expand their knowledge base and subsequently sustain competitiveness (Briggs, 2015). The idea has led to governments and organisations to place international R&D collaboration on their policy agenda. My interest is in to what extent can the knowledge created by international R&D collaboration benefit inventive output? Expanding the work of Briggs (2015), I divide cross-border collaboration into eight groups using World Bank's country classifications. The World Bank assigns a country to one of the following categories: (1) low-income country; (2) lower-middle income country; (3) upper-middle income country; (4) high-income country. The eight types of cross-border collaboration are formed based on different combinations of the World' Bank's country classifications: 1) collaboration between low income countries, between low and lower middle income countries, and between low and upper middle income countries; 2) collaboration between lower middle countries; 3) collaboration between lower middle and upper middle income countries; 4) collaboration between upper middle income countries; 5) collaboration between low and high income countries; 6) collaboration lower middle and high income countries; 7) collaboration between upper middle and high income countries; 8) collaboration between high income countries. I propose that knowledge created by the eight types of collaborations are varied in quality due to the disparity in the levels of absorptive capacity in different countries.

Compared with industrial organisations, universities may differ in cognitive attitudes and operational practices (Bonaccorsi and Thoma, 2007), resulting in knowledge-generation strategies that positively influence firms' innovative performance. My interest is in to what extent can the knowledge created by university collaboration benefit inventive output? Inspired by the research of Qiu et al. (2017), I divide university collaboration into domestic and international collaboration based on geographical proximity. The rationale behind such differentiation is that the nature of knowledge created by the two types of collaborations are different. For instance, while knowledge created by domestic university collaboration tends to be localised and cater to meet domestic firms' demand (Qiu et al., 2017), the knowledge created by international university collaboration tends to be distant, leading to radical innovations.

To investigate empirically above questions in the global context, this chapter employs a panel of joint patent data covering 80 countries from the EPO between 1987 and 2016. Patent quality is measured through the number of forward citations received: the higher the number of forward citations, the higher the patent quality.

The rest of the chapter is organised as follows. In Section two I present a detailed discussion of the relevant literature on cross-border and university collaborations. In Section three I then discuss the data and model used to study the effects of independent variables. In Section 4 I present the findings. Finally, In Section 5 I conclude the chapter with a discussion of the findings.

6.2 Literature review

6.2.1 International technological collaboration as a source of innovation

International technological collaboration is identified as one of the major three channels of knowledge diffusion (Montobbio and Sterzi, 2012). Whereas technological collaborations have been traditionally carried out between high income countries, there are indications that these collaborations are increasing seen between high income countries and lower income countries. Before continuing further, the concept of income groups should be clearly defined. The World Bank (2017) divides all countries[7] into four income groupings: low, lower-middle, upper-middle, and high. The division is based on income measured by gross national income per capita in U.S. dollars. The rationale for distinguishing between countries with income levels is that their capacity to absorb knowledge spillovers from collaboration may be different. Through high absorptive capacity and mature research networks, firms in developed countries may be better than firms in developing countries in terms of coordinating foreign collaborations, therefore may be able to exploit the knowledge from such collaborations more effectively.

Two schools of thought have conflicting views on the influences of co-owners' national income on the probability of trading. The first school of thought, represented by Linder Hypothesis (Linder, 1961), argues that countries with similar income levels possess overlapping demand (i.e. share similar consumer preferences), therefore international trade is more likely to occur between countries with identical preferences and endowments. Early studies (e.g. Patel and Pavitt, 1991) on the network of international technological collaborations pointed out that the level of innovation internationalisation was relatively small, heavily concentrated in the U.S., Japan, and developed European countries. These countries were among the most developed nations in the world in the 1990s. In addition, the gravity model of international trade (Tinbergen, 1962) suggests that countries with similar economic sizes (often measured in gross domestic

[7] Include all World Bank members, plus all other economies with populations of more than 30,000.

products) are more likely to trade with one another. Montobbio (2012) applies the gravity model to international patent collaborations, and find that emerging countries that share technological similarities are more likely to collaborate on technology.

The second school of thought (e.g. Gilsing et al., 2008; Wuyts et al., 2005) argues that collaborations between dissimilar but complementary partners can generate unique combinations of resources and knowledge that lead to valuable innovations. An example is the increasing number of technological collaborations between lower income countries and higher income countries. Several empirical studies suggest that such collaborations can generate international knowledge spillovers, which enables lower income countries to catch up with the higher income countries and to accumulate technological capabilities. Hu and Matthews (2005) show that international technology collaboration with high income countries greatly benefits the technology catching-up (in terms of patent counts) of medium income countries such as China. Investigating Chinese and Indian inventive teams, Branstetter et al. (2014) find that cross-border collaborations are more likely to produce valuable inventions (measured by forward citations received) than domestic collaborations in both countries. Analysing inventive activities between firms from Brazil, India, and China (BIC) and those from the European Union (EU), Giuliani et al. (2016) find that cross-border inventions between BIC firms and EU inventors are more valuable (in terms of forward citations received, size of patent family, patent's generality, as well as originality) than domestic ones.

6.2.2 University collaboration as a source of innovation

6.2.1.1 Knowledge spillovers from domestic university collaboration

Knowledge spillover from university research has widely seen as another critical source of innovation. In the economic geography literature, one school of thought believes that knowledge spillover is geographically bounded. In other words, geographic proximity is believed to be beneficial for successful knowledge creation. The rationale behind the argument is that the process of knowledge creation relies on interactive learning, which is embedded in a cultural and institutional environment. Since localised knowledge is supposed to be more aligned with local firm's demand (Arza, 2010), it is easier to absorb knowledge from local university collaborations than from distant university collaboration. Siegel et al. (2003) empirically show that firms located on university science parks in the United Kingdom have higher research productivity than those located outside university science parks, suggesting that geographical proximity to universities has real benefits. Analysing the role of geographical proximity in collaborative scientific research between universities and firms, Ponds et al. (2009) find that geographical proximity between universities and firms can complement the negative effects from the lack of institutional proximity. Qiu et al. (2017) find that domestic university collaboration has a larger positive impact on local firm's innovation than international university collaboration does.

6.2.1.2 Knowledge spillovers from international university collaboration

The opposing school of thought argues that geography is not a prerequisite for successful collaborations (e.g. Boschma 2005; Howells 2002; Malmberg and Maskell 2002). They suggest that geographical proximity plays an indirect role in positively influencing collaboration and knowledge exchange. Analysing the role of geographical distance on university-industry collaborations, Petruzzelli (2011) suggests that the geography is not a barrier in the collaborations between outstanding universities and firms. Anselin et al. (2000) suggest that geographical closeness to the universities do not benefit all firms as the knowledge spillovers emerged from domestic university collaborations are only at work to specific industries.

Compared with localised knowledge spillovers from domestic university collaborations, distant knowledge spillovers from international university collaborations tend to be more cutting-edge and basic research in nature (Qiu et al., 2017). For this reason, bridging knowledge gaps is often cited as the purpose for collaborations between developed and developing countries. International collaboration serves at least two purposes. First, advanced knowledge spillovers from developed countries creates opportunities for firms in developing countries to catch up with technological frontier of the world via influencing the learning and innovation capabilities of firms. Second, international collaboration gathers complementary knowledge resources from around the world and informs managers about technological trends and market demand. In addition, firms that collaborate internationally serves as a channel that enables other local firms to access advanced knowledge from the international university collaboration via disseminating to local industries.

6.3 Data

6.3.1 Source of Data

To investigate the research questions of interest, EPO Worldwide Patent Statistical Database, i.e. PATSTAT database (2017 Spring version) is used for retrieving joint patent data. PATSTAT provides detailed and rich information on patent holders' invention activities in 35 technical fields collected from more than 100 patent offices worldwide. PATSTAT is chosen for this study for the following reasons.

First, EPO is an important destination of patent filing as well as a popular route for inventors to seek for patent protection subsequently in other European countries. In recent years, the number of applications from China has been increasing rapidly. It is believed that only important inventions to be filed to EPO, considering the cost of patenting at EPO and the importance of Europe as a technology market; thus, collections of Chinese patents at the EPO should contain important inventions.

Second, the database updates its data every six months and it contains a significant number of variables that are useful in tracking innovation activities of the patentees, includes forward citations, backward citations, technology fields, and sectors of applicants, to name just a few.

The sample data contains 968,649 joint patent observations in 80 countries during the period 1987-2016. These exclude joint patents with three or more applicants, as there could be the problem of multiple partnerships behind such joint patenting. Figure 5.1 and 5.2 show the trends in joint patenting with universities, and with cross-border partners respectively. It appears that both types of joint patenting have been growing consistently over 1987-2011 and the numbers have doubled since 2012. Figure 5.3 shows the trend of cross-border joint patenting activities by the type of collaborations. Collaboration between high-income countries clearly dominate cross-border joint patenting activities.

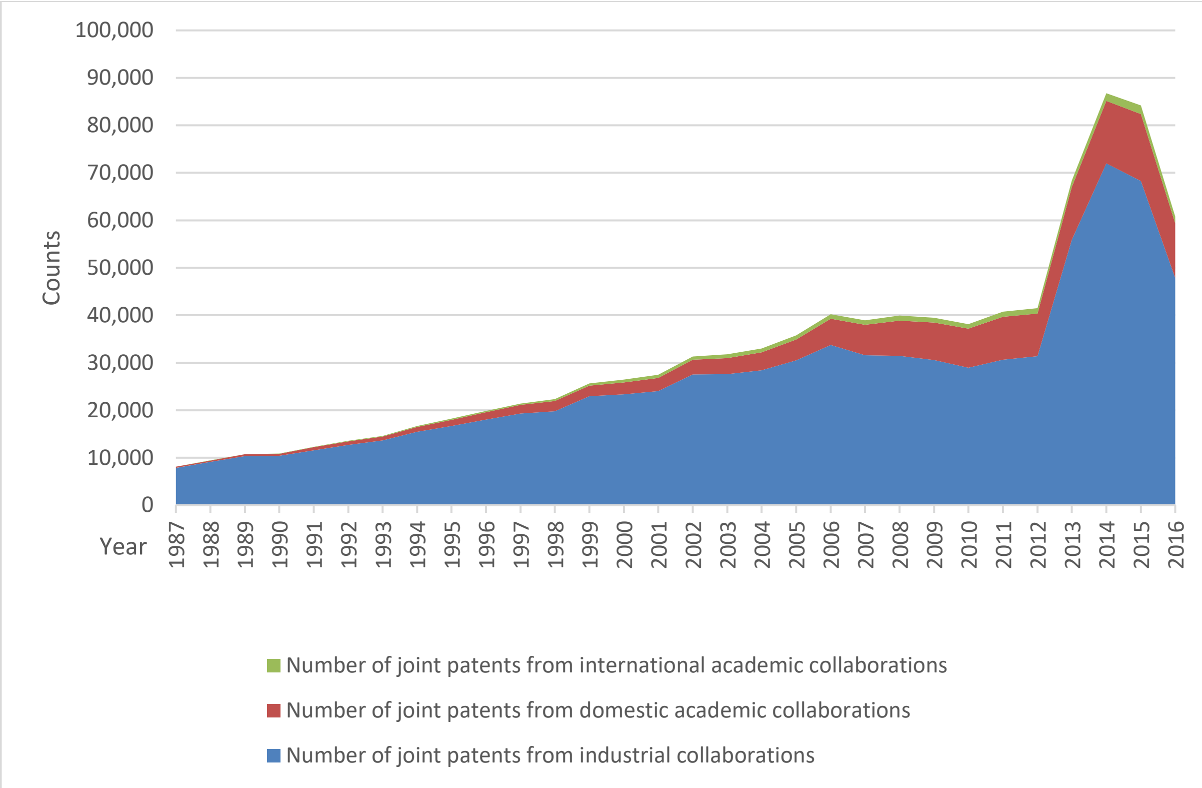

Figure 6. 1 Trends in joint patenting with universities

(Source: author's own calculation)

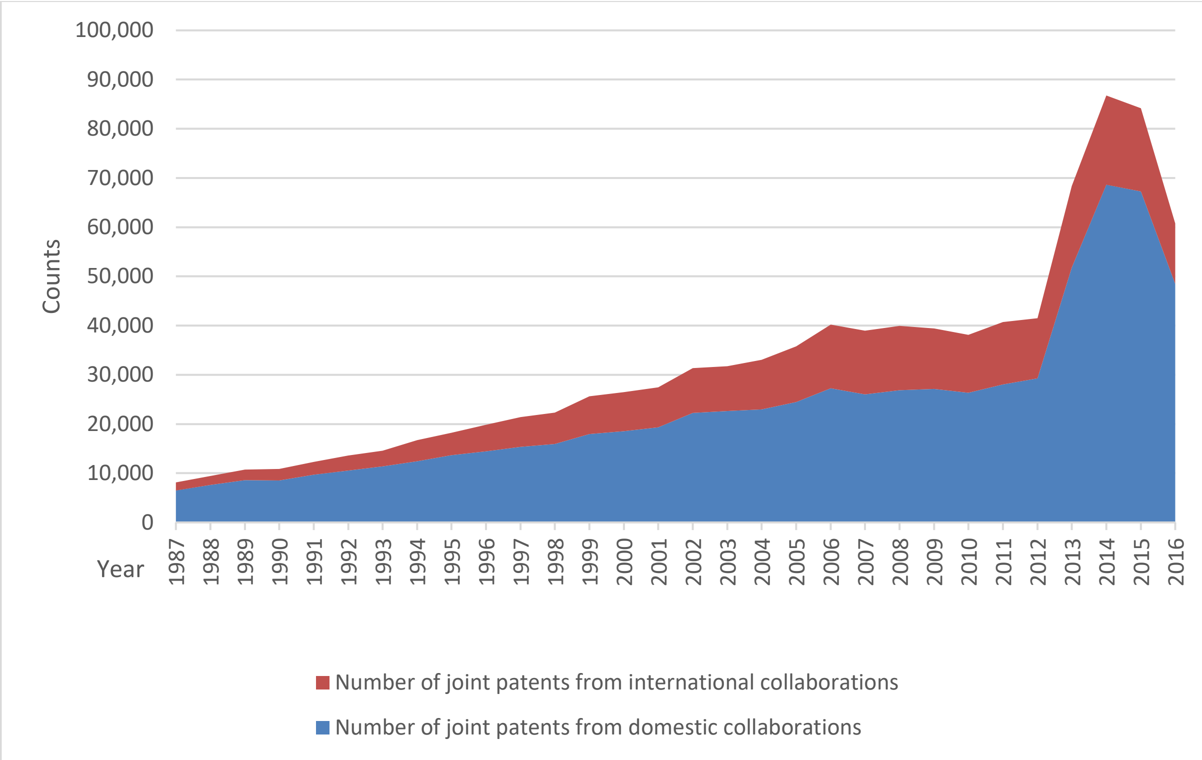

Figure 6. 2 Trends in joint patenting with cross-border partners

(Source: author's own calculation)

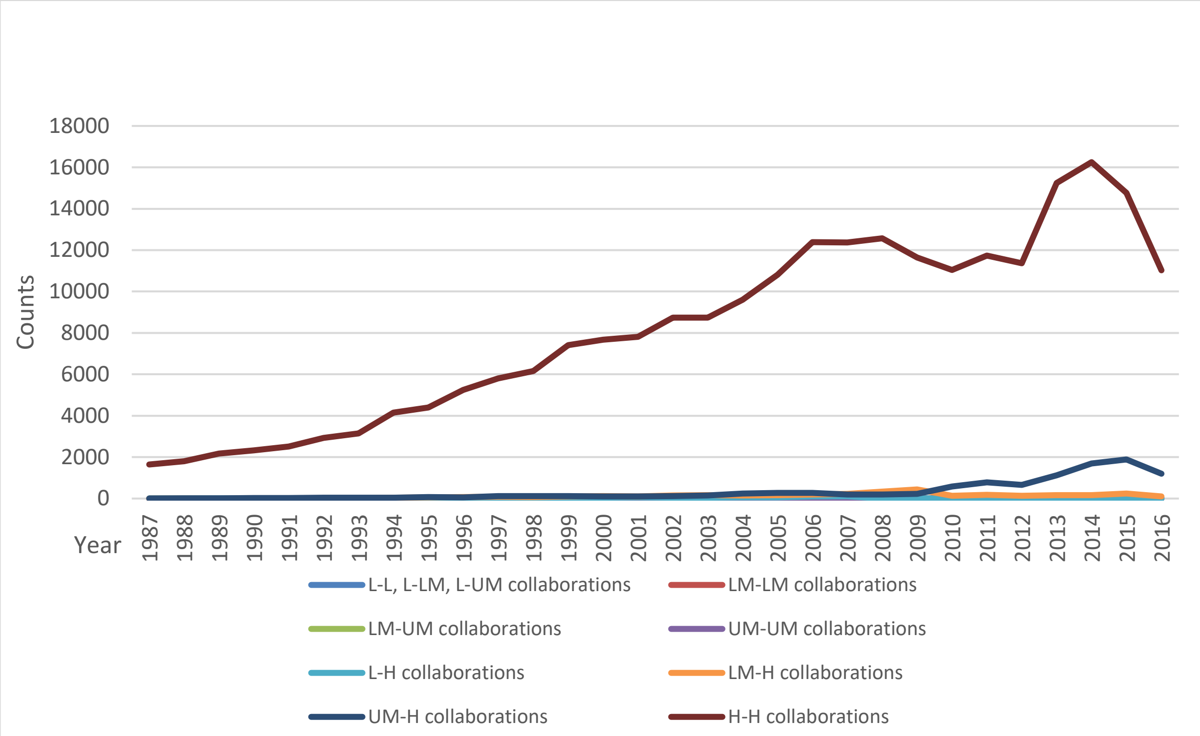

Figure 6. 3 Trends in cross-border joint patenting based on World Bank's country classifications

(Source: author’s own calculation)

6.3.2 Measures

6.3.2.1 Dependent variable

I use forward citations to proxy the quality of joint patents. Forward citation is widely used in innovation literature for a variety of purposes, including measuring firm innovative performance (Sampson, 2007), innovation impact (Miller et al., 2007), and innovation output (Singh, 2008). Trajtenberg (1990) found that forward citations are positively and significantly correlated with independent measure of returns from innovation. Hall et al. (2005) found that compared to those less frequently cited, patents with high citations are more likely to be profited from economic activities.

6.3.2.2 Independent variables

There are two explanatory variables considered to impact joint patent quality: 1) the presence of cross-border co-ownership; and 2) the presence of university co-ownership. The first independent variable of interest is whether the co-owners are originated from different countries. I construct a dummy variable that takes the value 1 if the joint patent is owned by firms in more than one country, and takes the value 0 if otherwise. Of the 968,649 joint patent observations in the sample, 26.7% have at least one collaborator that is originated from other countries.

The presence of a university co-owner is included as an explanatory variable in the empirical estimation. University partner is identified by the patent data via the variable ‘sector’. A dummy variable is constructed taking the value 1 if the joint patent is owned by a university partner, and 0 if otherwise. Of the 968,649 joint patent observations in the sample, 14.1% of which have at least one collaborator that is from a domestic university, and 2.1% of which have at least one collaborator that is from a foreign university.

6.3.2.3 Control variables

6.3.2.3.1 Country-level controls

To control for country specific effects on patent's value, I include two control variables.

LnIncome is the natural logarithm of income differences between international co-owners with the most disparate income levels (Briggs, 2015), measured by the absolute difference in GDP per capita of the two co-owners. It is likely that income differences between international co-owners impact joint patent quality, thus including this variable increases the robustness of the independent variables.

LnPatent is the natural logarithm of patent differences between international co-owners with the most disparate patent numbers. Data on GDP per capita in current US dollars and patent applications were obtained from the World Bank's World Development Indicators. This variable is expected to capture the country disparity in terms of technological development.

5.3.2.3.2 Patent-level controls

In line with the standard literature on patent-level regression analysis, I include the following control variables that might influence the patent's value: patent scope, number of inventors, number of backward citations, number of NPL citations, size of patent family and number of patent claims. Definition of these variables are covered in Chapter 3.

6.3.3 Econometric analysis

6.3.3.1 The model

The econometric model is specified as follows:

$Citations_i = \beta_0 + \beta_1 CrossBorder_i + \beta_2 University_i + + \beta_3 FamilySize_i + \beta_4\ PatentScope_i + \beta_5\ Inventors_i + \beta_6\ Backward_i + \beta_7 NPL_i + \beta_8 Claims_i + \epsilon_i$

where $Citations_i$ denotes the number of forward citations received within five years of patent publication; $CrossBorder_i$ indicates the presence of cross-border co-ownership. $University_i$ denotes the presence of university co-ownership. $Technologies_i$ represents the number of technology fields captured by the patent. $Inventors_i$ refers to the number of inventors worked for a given invention. $LnBackward_i$ denotes the number of patent literature cited by a given invention. $LnNPL_i$ refers to the number of scientific literature included in each patent application. $Claims_i$ defines the scope of the protection sought in a patent application.

6.3.3.2 Econometric methods

In this chapter, econometric models for count data include PQGPMLE (benchmark model), NB1 (main model), and NB2 (robustness checks). These are covered in Chapter 3.

6.4 Results

This section presents the benchmark results before discusses the main results, and concludes by reporting the robustness test. All the results are reported in marginal effects. As explained in the previous chapter, when it comes to nonlinear models, it is more straightforward to interpret the results via the interpretation of marginal effects than direct interpretation of coefficients. It would be of interests to look at the AME, which first aggregates all individual responses and then calculates the average response. Tables 6.1 presents the summary statistics for the sample.

Table 6. 1 Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Forward citations	968,649	1.21874	4.492274	0	654
University co-ownership					
(1) Domestic university collaboration	136,795	0.14122	0.348251	0	1
(2) International university collaboration	20,046	0.02069	0.142361	0	1
Cross-border co-ownership				0	1
(I) L-L, L-LM, L-UM	12	1.24E-05	0.00352	0	1
(II) LM-LM	54	5.57E-05	0.00747	0	1
(III) LM-UM	141	0.00015	0.01206	0	1
(IV) UM-UM	86	8.88E-05	0.00942	0	1
(V) L-H	705	0.00073	0.02697	0	1
(VI) LM-H	3,629	0.00375	0.06109	0	1
(VII) UM-H	10,476	0.01082	0.10343	0	1
(VIII) H-H	243,461	0.25134	0.43378	0	1
LnIncome	968,106	2.37165	3.98343	0	11.87815
LnPatent	898,633	2.95773	4.94709	0	13.783
LnBackward	968,649	1.01107	1.08212	0	6.91869
LnNPL	968,649	0.32185	0.74946	0	6.35437
Inventors	968,649	3.75076	2.48952	0	98
Patent family size	968,649	6.00921	7.23878	1	235
Patent claims	968,649	3.47025	7.99058	0	442
Patent scope	968,649	1.57754	0.83333	0	13

6.4.1 Benchmark results

Table 6.2 reports the benchmark results for the Poisson quasi-generalized pseudo-maximum likelihood estimator with robust standard errors (i.e. PQGPMLE).

Table 6. 2 Benchmark results of PQGPMLE

VARIABLES	I PQGPMLE	II PQGPMLE	III PQGPMLE	IV PQGPMLE
Domestic university collaboration		0.343*** (0.099)		0.396*** (0.104)
International university collaboration		-0.220 (0.204)		-0.031 (0.211)
(I) L-L, L-LM, L-UM			0.514 (5.000)	0.589 (5.147)
(II) LM-LM			-5.617*** (1.433)	-5.721*** (1.477)
(III) LM-UM			-1.245 (2.276)	-1.212 (2.347)
(IV) UM-UM			-3.062 (2.131)	-3.078 (2.203)
(V) L-H			27.582*** (5.247)	28.508*** (5.419)
(VI) LM-H			16.215*** (2.740)	16.774*** (2.833)
(VII) UM-H			4.353*** (1.041)	4.552*** (1.077)
(VIII) H-H			11.308*** (1.801)	11.721*** (1.864)
LnIncome	-0.230*** (0.040)	-0.229*** (0.040)	-0.661*** (0.091)	-0.674*** (0.093)
LnPatent	0.290*** (0.042)	0.298*** (0.043)	-0.009 (0.030)	-0.010 (0.031)
LnBackward	5.960*** (0.739)	6.097*** (0.759)	6.044*** (0.753)	6.194*** (0.774)
LnNPL	0.834*** (0.107)	0.820*** (0.107)	0.856*** (0.110)	0.834*** (0.109)
Inventors	0.317*** (0.041)	0.322*** (0.042)	0.333*** (0.043)	0.338*** (0.044)
Patent family size	-0.062*** (0.010)	-0.063*** (0.010)	-0.069*** (0.011)	-0.071*** (0.011)
Patent claims	0.258*** (0.036)	0.264*** (0.037)	0.262*** (0.036)	0.268*** (0.037)
Patent scope	0.805*** (0.103)	0.820*** (0.105)	0.814*** (0.104)	0.828*** (0.107)
Observations	898,326	898,326	898,326	898,326

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As robustly shown across all columns of Table 6.2, domestic university collaboration has a positive and statistically significant impact ($p<0.01$) on forward citations received, other factors being constant. Specifically, domestic university collaboration is found to benefit joint patent quality by increasing between 0.3 to 0.4 forward citations. International university collaboration is negatively associated with forward citations, but the effect is insignificant.

The benchmark results show that different types of cross-border collaboration vary in their effect on forward citations. Compared with the coefficient of domestic collaboration (base group), the coefficient of type I collaboration is insignificant although positive. The coefficients of type III and IV collaborations are insignificant although negative. Type II, representing LM-LM collaboration, has a negative and statistically significant effect ($p<0.01$) on forward citations; in other words, LM-LM collaborations are not conductive to high quality patents. Type V, VI, VII, and VIII collaborations are found to be having a positive and statistically significant effect ($p<0.01$) on forward citations, meaning that these types of collaborations yield high quality patents. Type V collaboration has the largest positive effect, followed by type VI, type VIII, then type VII. To summarise, it emerges that the collaborations between low-income countries and lower-middle income countries are less effective in generating high quality inventions, whereas collaborations between higher income countries.

As far as the control variables are concerned, the effect of income differences between partners countries and the size of patent family are negative and statistically significant ($p<0.01$) on forward citations. The remaining variables, namely differences in patent applications between partner countries, backward citations, NPL citations, number of inventors, number of patent claims, as well as the breadth of patented application, are all showing positive and statistically significant effect ($p<0.01$) on forward citations.

6.4.2 Main results and discussion

Table 6.3 reports the main results for Negative Binomial regression model with linear variance function (i.e. NB1), estimating the probability that a joint patent is high quality.

Table 6. 3 Main results of NB1

VARIABLES	I NB1	II NB1	III NB1	IV NB1
Domestic university collaboration		0.056***		0.061***
		(0.008)		(0.008)
International university collaboration		-0.034*		-0.018
		(0.020)		(0.020)
(I) L-L, L-LM, L-UM			0.432	0.444
			(1.037)	(1.045)
(II) LM-LM			-0.603**	-0.596**
			(0.275)	(0.278)
(III) LM-UM			0.171	0.182
			(0.282)	(0.284)
(IV) UM-UM			-0.289	-0.280
			(0.305)	(0.308)
(V) L-H			3.387***	3.416***
			(0.300)	(0.302)
(VI) LM-H			2.361***	2.381***
			(0.154)	(0.155)
(VII) UM-H			0.962***	0.974***
			(0.087)	(0.088)
(VIII) H-H			1.680***	1.695***
			(0.086)	(0.087)
LnIncome	-0.064***	-0.063***	-0.126***	-0.126***
	(0.003)	(0.003)	(0.003)	(0.003)
LnPatent	0.063***	0.064***	0.006*	0.006*
	(0.002)	(0.002)	(0.003)	(0.003)
LnBackward	0.726***	0.728***	0.727***	0.731***
	(0.005)	(0.005)	(0.005)	(0.005)
LnNPL	-0.020***	-0.023***	-0.017***	-0.021***
	(0.005)	(0.005)	(0.005)	(0.005)
Inventors	0.028***	0.028***	0.030***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent family size	-0.032***	-0.032***	-0.033***	-0.033***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent claims	0.016***	0.016***	0.016***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent scope	0.097***	0.097***	0.097***	0.097***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	898,326	898,326	898,326	898,326

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As demonstrated across all columns of Table 6.3, domestic university collaboration has a positive and statistically significant impact ($p<0.01$) on forward citations received, other factors being constant. Specifically, domestic university collaboration is found to benefit joint patent quality by increasing 0.1 forward citation, which in practical term is less than that reported by the benchmark results (0.3-0.4 forward citations). Column II shows that the coefficient of international university collaboration is weakly significant but negative ($p<0.1$); the coefficient becomes insignificant although negative in the full model (Column IV).

The result echoes with those of a large body of prior literature finding the positive impact of proximity on innovative activities. Glaeser, Kallal, Scheinkman and Shleifer (1992, p.1126) argues that "intellectual breakthroughs must cross hallways and streets more easily than oceans and continents." Feldman (1994a and 1994b) suggests that geographical proximity mitigates uncertainty of innovative activity through enhancing the ability of firms to exchange ideas. Comparing the probabilities of patents citing prior patents with inventors from the same city against a randomly drawn control sample of patents, Jaffe, Trajtenberg and Henderson (1993), Almedia and Kogut (1997), and Jaffe and Trajtenberg (2002) all find that patent citations are significantly more localized than the control group, indicating that geographical proximity is crucial in transmitting and exploiting knowledge.

As for cross-border collaborations, the finding is similar to that of benchmark results. First, compared with the coefficient of domestic collaboration (base group) the coefficient of type II collaboration is negative and statistically significant ($p<0.05$). In practical terms, the collaboration reduces forward citation by 0.6-0.7 units. Second, the coefficients of type V, VI, VII, and VIII are statistically significant and positive ($p<0.01$); yet, the effects are much smaller compared with those reported by the benchmark results. Specifically, type V (low-income country and high-income county) collaboration is found to increase the forward citation by approximately 3.4; type VI (lower-middle income country – high income country) collaboration by about 2.4; type VII by 1; and type VIII by about 1.7. This finding agrees with the argument that interactions between heterogeneous partners can form unique combination of resources and knowledge that generates novel inventions (Gilsing et al., 2008; Wuyts et al., 2005). The finding also supports that of Guan and Chen (2012) and Hu and Matthew (2008) that emerging countries can benefit greatly from the international collaboration with developed countries.

As far as the control variables are concerned, the findings are largely consistent with the benchmark results reported in Table 6.2. The exception is that the coefficient of NPL citation changed from positive (Table 6.2) to negative (Table 6.3) although remains statistically significant ($p<0.01$).

Results show that income difference and patent difference are not mirroring each other. The coefficient of income difference between partner countries is negative and statistically significant ($p<0.01$); the variable is found to decrease forward citation by 0.1 unit. The coefficient of patent application difference between partner countries is statistically significant and positive (p<0.0.1) for Columns I and II, but weakly significant although positive ($p<0.1$) for Columns III and IV; the variable is shown to increase forward citation by approximately 0.1 unit. The result suggests that level of economic development does not reflect level of technological development. High income countries are not necessarily those technology-leading ones - they vary in their innovative capacity, which is closely related to patenting.

The coefficient of backward citation is statistically significant and positive; the variable is found to increase 0.7 forward citations. Coefficients of the number of inventors, patent claims, and patent scope all show positive and statistically significant effects ($p<0.01$) on forward citation, but the effect in practical term is trivial (less than 0.1 increase in forward citation). The same is observed for the effect of size of patent family: the coefficient of the variable is negative and statistically significant ($p<0.01$), yet the effect is practical terms is trivial (less than 0.1 decrease in forward citation).

To summarise, the consistent outcome is domestic university collaboration is strongly correlated to joint patent quality (using forward citations). The positive effect of cross-border collaboration is most significant for type V (collaboration between low-income country and high-income country), then type VI (collaboration between lower-middle income country and high-income country), type VIII (collaboration between high-income county and high-income country), then type VII (collaboration between upper-middle income country and high-income country). As far as the control variables are concerned, the results are consistent with those reported by benchmark results in Table 6.2, though the effects in practical terms are relatively smaller.

6.4.2 Robustness test

I further compare the main results with those estimated by the Negative Binomial regression model with quadratic variance function (NB2: Table 6.4).

Table 6. 4 Robustness test by NB2

VARIABLES	I NB2	II NB2	III NB2	IV NB2
Domestic university collaboration		0.056***		0.061***
		(0.008)		(0.008)
International university collaboration		-0.034*		-0.018
		(0.020)		(0.020)
(I) L-L, L-LM, L-UM			0.432	0.444
			(1.037)	(1.045)
(II) LM-LM			-0.603**	-0.596**
			(0.275)	(0.278)
(III) LM-UM			0.171	0.182
			(0.282)	(0.284)
(IV) UM-UM			-0.289	-0.280
			(0.305)	(0.308)
(V) L-H			3.387***	3.416***
			(0.300)	(0.302)
(VI) LM-H			2.361***	2.381***
			(0.154)	(0.155)
(VII) UM-H			0.962***	0.974***
			(0.087)	(0.088)
(VIII) H-H			1.680***	1.695***
			(0.086)	(0.087)
LnIncome	-0.167***	-0.063***	-0.126***	-0.126***
	(0.032)	(0.003)	(0.003)	(0.003)
LnPatent	0.214***	0.064***	0.006*	0.006*
	(0.032)	(0.002)	(0.003)	(0.003)
LnBackward	5.639***	0.728***	0.727***	0.731***
	(0.687)	(0.005)	(0.005)	(0.005)
LnNPL	1.197***	-0.023***	-0.017***	-0.021***
	(0.149)	(0.005)	(0.005)	(0.005)
Inventors	0.259***	0.028***	0.030***	0.029***
	(0.033)	(0.001)	(0.001)	(0.001)
Patent family size	-0.089***	-0.032***	-0.033***	-0.033***
	(0.012)	(0.001)	(0.001)	(0.001)
Patent claims	0.220***	0.016***	0.016***	0.016***
	(0.030)	(0.001)	(0.001)	(0.001)
Patent scope	0.714***	0.097***	0.097***	0.097***
	(0.090)	(0.004)	(0.004)	(0.004)
Observations	898,326	898,326	898,326	898,326

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Here, the consistent outcome is the coefficient of domestic university collaboration remains statistically significant and positive. Compared with the coefficient of domestic collaboration (base group), coefficients of type V, VI, VII, and VIII collaborations are positive and statistically significant, which are consistent with those reported by the benchmark and main results. As far as the control variables are concerned, the coefficients of all the control variables are consistent with the benchmark and main results.

To summarise, results of NB2 shows consistent findings as with NB1, confirming the robustness of the main results.

6.5 Chapter summary

Since the 1980s, the number of inter-firm collaborations has been growing (Hagedoorn et al., 2003). In these partnerships, international collaboration and university collaboration are often considered effective strategies to acquire cutting-edge technology, tacit knowledge, and diverse skills possessed by potential partners. If patent is the output of these collaborations, then patent that are jointly assigned to collaborative partners should be effective measures of innovative output resulting from the collaborations (Kim and Song, 2007). Given the importance of joint R&D in inter-firm collaboration, it is important for both firm manager and policymakers to recognize the growing importance of joint patenting in patenting activity, and to understand how joint patenting can facilitate novel innovations.

Employing forward citations as the measure of joint patent quality, I investigate how different types of cross-border and university collaborations influence the quality of joint patent using a larger sample covering joint patent observations of 80 countries for the period 1987-2016. My research distinguishes university collaborations into domestic and international types, and categorizes cross-border collaborations into several groups (i.e. L-L, L-LM, L-UM, LM-LM, LM-UM, UM-UM, L-H, LM-H, H-H, and UM-H), based on the World Bank’s country classifications.

It emerges that collaborations between low-income countries is negatively associated with joint patent quality. The quality of joint inventive activities of these countries call for attention and policy review.

The positive effects of cross-border joint patenting activities are most pronounced for collaborations involve high-income countries. These countries have greater levels of R&D activities than lower income countries, as evident by the number of joint patents. R&D activities can increase the absorptive capacity of firms, which is believed to be key to high innovation performance.

The result that domestic university collaborations and international university collaborations differ in their capacities to influence joint patent quality is consistent with the finding of Qiu et al. (2017) that domestic university collaboration has a larger positive impact on local firm's innovation, but contradicts with that reported by Giuliani et al. (2016), who report the opposite finding. This might be that knowledge generated from collaboration with domestic universities are more approachable and aligned with the demand of domestic firms. This results also suggest that knowledge emerged from university collaborations are geographically bounded.

These findings contribute to a better understanding of the joint patenting activities by countries who have joint patent filings in the European Patent Office. First, this work is the first attempt to differentiate cross-border collaborations into eight types using World Bank's country classification methodology. Such differentiation allows us to further understand the dynamics within cross-border collaborations. My findings highlight the types of collaborations that contribute towards higher patent quality and those do not.

Second, this research is original in classifying university collaborations into domestic and international ones. Extant research (e.g. Briggs, 2015) studies the joint patenting between universities and firms without differentiating the nature of university collaborations. Such differentiation allows us to compare the innovative outputs of international and domestic university collaborations. Overall, the results show that domestic university collaborations have a larger positive effect on joint patent quality compared to the international ones.

Finally, this study is original in including patent-level characteristics into estimation analysis. This expands the work of Briggs (2015) who investigates country-level characteristics and joint patent value. The inclusion of the patent-level variables controls for the factors that are identified in the patent value literature, therefore improving the robustness of this research.

This study has implications for practitioners. First, since the results show that domestic university collaborations are more effective in producing higher quality patents, I posit that S&T policies could promote further the R&D linkages between domestic universities and firms. Second, since the results show that types of cross-border collaboration could differ in their capacities to influence innovative output, policy makers should take these into consideration when they design innovation policies.

Chapter 7 Proximity in Industry-University Collaborations

7.1 Introduction

Since the late 20th century, innovation has been the key to increase profits and market share (Pisano and Teece, 2007), as well as an important source of firm's sustained competitive advantage (Johannessen and Olsen, 2010). Driven by profit-maximisation, firms are naturally interested in the economic value created from innovation activities, as it is crucial for firms' survival and development. Appropriating economic returns from innovation, however, remains a challenge to many firms.

Previous studies offered lots of insights on the problem. Before the 2000s, most work focused on building barriers around innovations for more economic returns. These barriers, in the form of legal protection (such as patent and trademark), are believed to protect firms from leaking core knowledge to imitators. At that time, R&D was internal activities of firms. It was thought that whichever firm discovers, develops, and commercializes an innovation in the first instance, that firm can profit from innovation (Chesbrough, 2006). As innovation activities were carried out within firm's own boundaries, such innovation was said to be 'closed innovation'. In the early 2000s, improved mobility of skilled workers, improved capabilities of suppliers, as well as shortening in product cycle call for a change to the mode of innovation. Thereby, the era of 'open innovation' began, witnessing the rise of external R&D and use of R&D collaboration in firms' innovation activities.

Previous studies offered several explanations on the relationship between R&D collaborations and the innovation outcomes, include collaboration governance (e.g. Lee and Cavusgil, 2006), R&D experience (e.g. Hoang and Rothaermel, 2005), and partner characteristics (e.g. Saxton, 1997). However, research on inter-organisational determinants remains relatively scarce – the proximity dimensions in particular. The effect of proximity is mixed in the empirical literature. On the one hand, it can smooth coordination and facilitating interactive learning (Capaldo and Petruzzelli, 2014), on the other hand, it may hinder innovation by nurturing ‘competency trap’ (Boschma, 2005). In an attempt to contribute to the understanding of proximity in collaborations, I propose a study to investigate the effect of proximity dimensions on the value of joint innovation. In particular, I am interested in looking at the R&D collaborations between firm and university in an emerging country – China.

This chapter intends to provide an analysis of how proximity dimensions affect the value of collaboration between firm and university. Specifically, the chapter looks at the roles of cognitive proximity and organizational proximity in shaping the innovation performance of firm-university collaboration. In this chapter, firm takes a leading role in innovation. I use patent data from the European Patent Office to investigate the problem. The dependent variable of the study is patent’s forward citations, which indicates the economic value of joint patent. Cognitive proximity refers to the degree of knowledge similarity between firm and university. In this paper, it is used to indicate firm’s experience in developing joint patents with universities. In the empirical analysis, it is measured by the ratio of jointly owned patents with universities. ‘Organisational proximity’ is measured by a dummy that indicates whether a firm and its university partner are from the same organisation. The organisation of the chapters is as follows. Section two presents an analysis of industry-university relations in China. Section three discusses the role of proximity in firm-university collaborations in China, then proposes two hypotheses concerning cognitive and organisational proximity. Section four presents the data and methodology of this chapter. Section five discusses the findings of this study. Section six analyses the findings. Section seven concludes the chapter and discusses the implications of findings.

7.2 Industry-University Relations in China

7.2.1 Industry-University Interactions in the Planned Era (1953-1978)

In the planned era, the division of research and manufacturing was clear-cut. State-owned enterprises (SOEs) were excluded from the value-added chain. It was the ministries in charge of these firms that made strategic decisions on firms' internal businesses such as company strategy, R&D, and marketing activities. As a result of political decisions, the academia took up the market research and produced the final products that firms could reproduce on a larger scale (Eun et al., 2006). During the period 1987-1999, the innovation capabilities of universities were strengthened and they became the main entity of innovation (Lei and al., 2011). The SOEs, in contrast, remain relatively weak in innovations, due to lack of knowledge about the market and basic research, and other institutional reasons. Due to the above reasons, communication between industry and universities in China was limited during the planned era. By the early 1990s, the desire of industry to collaborate with universities on innovations remained low, according to a survey conducted by Guan et al. (2005). Historically, SOEs had their R&D department and preferred to use their own R&D findings. In contrast, private firms did not have their R&D departments, and there was no channel for these firms to absorb the R&D results of universities. Furthermore, most research activities of universities at the time were research-oriented and rarely considered the market need. Consequently, the communication between industry and academia was so limited that the latter could not provide support for backing commercialization with scientific discoveries.

7.2.2 Industry-University Interactions in the post-reformation era (1978-present)

The era of reformation witnessed the growth in collaborations between the academia and industry. The survey of Guan et al. (2005) revealed that there are six collaboration channels in firm-university collaboration in China. To both large firms and high-tech firms, R&D

collaboration has been ranked as the first channel of knowledge transfer between firm and university. The second and third places are taken by employing R&D personnel from universities, and entrust R&D tasks to universities. Other channels, such as ‘purchase R&D results directly from universities’, ‘establish R&D organisations with universities’, and ‘participate in joint national projects with universities’ are weighted differently by large firms and high-tech firms. R&D collaboration is popular because it is win-win to both parties. To universities, collaboration not only tests the applicability of scientific knowledge in industrial innovation, but also serves as a basis for attracting industrial funds to support new scientific research. To firms, collaboration not only addresses their technological needs, but also accumulates knowledge and capabilities through communicative learning.

7.2.3 The Establishment of University Enterprises

In the history of industry-university collaboration, the establishment of university enterprises (UEs) is an important event. In China, UEs cannot be equated with university spin-offs (Eun et al., 2006), which usually set up by individual academics with personally raised funds and ‘off-duty inventions’ (Roberts, 1991). In contrary, UEs in China are established, funded, and managed by the mother institutions. The innovation activities of UEs are largely dependent on the capabilities of the mother institution.

The first stage of UE development in China is analogous to the scenario proposed by the ‘Triple Helix’ scholars, who argue that academia should be closely linked with industry in order to maximize ‘capitalisation of knowledge’ (Etzkowitz, 1998; 2002). The ‘National Torch Program’ enacted in 1988 and the improved economic conditions at the time jointly pushed the transformation of technology into production. Under such atmosphere, universities were encouraged to participate in the commercialized activities (Lei et al., 2011). In 1995, when ‘Resolution on Accelerating S&T Development’ was enacted, the message from the central government was that universities should establish high-tech firms using their own S&T capacity (Eun et al., 2006), and linkages between the academia and industry should be formed and promoted further. Thanks to the supportive environment and enhancing innovation capacity of universities, many UEs were established between early 1990s and early 2000s. Using patent statistics, Lei et al. (2011) showed that universities and research institutes accounted for half of the top ten patent assignees and was the major entity of innovation during the period 1987 – 1999. By the end of 2001, there were 5039 UEs throughout China (Eun et al., 2006) and about 40 of them were already listed on the stock markets in Mainland China and Hong Kong. All these suggest that universities are not only places for learning and basic research in China, but also places for generating commercial knowledge for industry.

The second stage of UE development in China is similar to the phenomenon depicted by scholars of 'New Economics and Science', which suggests that the academia and industry are organizationally and functionally different from each other, hence a clear division of labour between the two should be in place in order to maximize the benefits to the society. In 2001, the issue of 'Memorandum on the Experiment of Standardizing University-run Enterprises Management at Peking University and Tsinghua University' signaled a shift of attitude of the central government towards the management of UE: UEs are called to separate from their mother institutions. As a consequence, the development of UEs was slowed down and the number of UEs decreased to 4563 in year 2004. UEs were found to raise less capital through stock markets and the financial performance of many listed UEs have been unsatisfactory (Eun et al., 2006). It appears that the separation of UEs from their mother institutions to some extent, has reshuffled the innovation system of China, but at the expense of phasing out some UEs.

The above discussion has shown that the relationship between university and industry has evolved from 'distant' to 'close' in the past 50 years. From a separate research function of the nation to a major innovator that bridges academia and industry, university as an important innovator of China has never been so intertwined with the nation's innovative activities.

7.3. Proximity in Industry-University Collaboration in China

Scholars suggested that proximity dimensions are important facilitators of inter-organisational collaboration (Kabo et al., 2014; Steinmo and Rasmussen, 2016). In particular, dimensions such as cognitive proximity can converge knowledge of partner organisations and enhance the speed and efficiency of absorbing new knowledge (Wuyts et al., 2005); organizational proximity, not only coordinates the exchange of complementary knowledge, but also enables the transfer of such information in times of uncertainty (Monge et al., 1985); social proximity that encourages an open attitude that is built on rationality rather than pure profit maximization, can enhance interactive learning and innovative performance (Agrawal et al., 2008); institutional proximity, influences the level of knowledge transfer, interactive learning, and innovation between organisations that share the same institutional rules as well as cultural values (Zukin and Dimaggio, 1990); geographical proximity, facilitates the exchange of tacit knowledge by forming knowledge clusters that are geographically bounded (Katz, 1994).

Although universities are potentially valuable collaboration partners for developing innovations, not all the firms find it easy to maintain the relationships with universities and capture values from joint innovations. Proximity, being an important facilitator of inter-organisational collaboration, is therefore an important topic in industry-university collaborations. However, it remains unknown that how proximity dimensions jointly shape the outcome of university-industry interaction. In an attempt to contribute to current understanding of this question, I explore two dimensions of proximity: cognitive and organizational[8].

[8] Other dimensions were not discussed due to limitation of data.

7.3.1 Cognitive Proximity

Because outcomes of knowledge searching are often uncertain and unexpected, firms conduct routinized behaviour in order to minimise risks (Nelson and Winter, 2009). This suggests that knowledge creation is cumulative outcome of knowledge processes within firms. In the context of open innovation, knowledge creation and innovations require the combination of diverse, heterogeneous, and complementary capabilities of different partners (Nooteboom, 2000). However, this is no easy task. Because knowledge is idiosyncratic to firms that created it, without sufficient absorptive capacity, which is dependent on the technical competencies that firms possess (Boschma, 2005), knowledge transfer is unlikely to benefit firms that in need of new technology. When absorptive capacity is insufficient, the costs that firms use to acquire knowledge will rise (Perez and Soete, 1988). This is because, in the course of knowledge search, there is always a minimum level of knowledge that firms are unable to absorb quickly hence firms need to invest in the required knowledge of each new technology (Boschma, 2005). To industrial firms, it appears that lacking knowledge of basic science is the root cause of knowledge gap. Since basic science is universities' natural domain, they can complement firms' absorptive capacity by contributing quality research personnel and bridging firms' knowledge gap via information exchange. In the view of proximity theorists, organisations that share identical knowledge bases can learn from each other quickly and efficiently. This suggests that in firm-university collaborations, the closer the knowledge base between firm and university, the higher the collaboration performance.

However, too much cognitive proximity can cause harm to innovation. On the one hand, close cognitive distance facilitates learning; on the other hand, it limits the potential for developing further absorptive capacity. Moreover, cognitive proximity may lead to cognitive lock-in (Boschma, 2005), which means that development of new technologies is hampered by routinized behaviour. In the long-term, too much cognitive proximity will burden firms and lead to the so-called 'competency trap' (Levitt and March, 1996), which can be difficult for firms to unlearn routines that have been successful in the past. Furthermore, too much cognitive proximity may increase the risks of knowledge leakage. In the case of collaborating with competitors, where the cognitive distance is close, competing firms may be reluctant to share knowledge for fear of losing competitive capabilities. However, according to the knowledge spillover theories (e.g. Acs et al., 2009), knowledge cannot always be kept inside the firm boundaries; it will gradually spill over across organisations. Hence, there exists a certain level of risks if the collaborative partners share too much cognitive proximity.

Summarizing the above discussion, I argue that in order to facilitate effective learning, a certain level of cognitive distance between partners is required; however such level has to be maintained at a moderate level for the sake of enhancing organisations' absorptive capacity and protecting their core knowledge. For these reasons, I believe that the positive impact of cognitive proximity on the collaboration outcome will start to diminish at a certain point. That is to say, the relationship between level of cognitive proximity and the collaboration outcome is curvilinear, which displays as an inverted-U shape.

> *Hypothesis 1. Cognitive proximity has a curvilinear effect on firm-university collaboration performance.*

7.3.2 Organisational Proximity

In addition to a common knowledge base that is important for bringing firms together for interactive learning, a capacity to coordinate the exchange of complementary knowledge within and between organisations (Boschma, 2005) is also necessary. Organisational proximity refers to the scenario where partners are governed by "a relationship of financial and economic dependence or interdependence" (Kirat and Lung, 1999). Such relationship can either be within (i.e. intra-organisational) or between (i.e. inter-organisational) organisations. In the case of firm-university collaboration, I am interested to know if a focal firm is affiliated to its university partner (i.e. a spinoff).

Our review of the literature reveals that researchers' opinions are divided over whether R&D agreement between different units of an organisation can be seen as collaboration or not. While some made explicit distinctions between R&D contracts within a large organisation and R&D collaborations between different organisations (e.g. Archibugi, 2004), some include 'within the group' collaboration as collaboration (e.g. Loof, 2009). I agree with the latter opinion that intra-organisational co-practice is also collaboration and the reasons are listed as follows. First, organisations, especially large organisations, are differed in the level of integration of their subsidiaries (Almeida et al., 2002). This is because heterogeneous strategies, incentives, and capabilities of units can make technological integration a very challenging task (Frost and Zhou, 2005). For this reason, collaboration within the same organisation can be as problematic as collaboration with external partners. Second, according to my knowledge of the data, there is some degree of organizational separation between a focal firm and a university. It may be true that spinoffs rely on university's capability at the early stage of their establishment, however technological capabilities of the spinoffs can develop and accumulate to new levels, and that their focuses and strategies may evolve and eventually divert from its parent organisation, i.e. university. Under this consideration, there should exist some degree of organizational separation between spinoff and university.

Because knowledge creation and innovations often involve uncertainty and opportunism, organisations are increasingly resorting to partnering with organisations that share similar knowledge base and company culture. Having organizational connection with partners is beneficial for knowledge creation and innovations because within an organisation, there is centralized coordination that brings together different units (Lawson and Lorenz, 1999) and facilitates the transfer of complex knowledge between them (Hansen, 1999). Strong ties are better than weak ties because the former are more likely to offer solutions and feedback, which can enhance the knowledge transfer. However, there are opposing views that too much organizational proximity could affect learning and innovation by reducing flexibility (Capaldo and Petruzzelli, 2014). In the views of the authors, the cognitive dimension of organizational proximity suggests that the adverse effect of it can be addressed by grouping together people with a certain level of cognitive proximity. Such intra-organizational arrangement can overcome the issue of too much proximity, hence the benefits of organizational proximity outweigh its adverse effects. Under this consideration, I believe that:

> *Hypothesis 2. Organisational proximity has a positive effect on firm-university collaboration performance.*

7.4 Data

7.4.1 Source of data

R&D and patent variables are widely used in innovation studies (e.g. Wu and Shanley, 2009). While R&D data is privately kept to companies, patent information is publicly available. Compared with R&D indicators such as R&D personnel and R&D expenditure, patent has a wider coverage because it not only indicates the quality of the R&D input, but also provides a direct measure of the R&D output. Considering these aspects, patent data is chosen for analysis purpose.

EPO Worldwide Patent Statistical Database, i.e. PATSTAT database (2017 Spring version) is thus used for retrieving joint patent data. The database provides detailed and rich information on patent holders' invention activities in 35 technical fields collected from more than 100 patent offices worldwide. PATSTAT is chosen for this study for the following reasons. First, EPO is an important destination of patent filing as well as a popular route for inventors to seek for patent protection subsequently in other European countries. In recent years, the number of applications from China has been increasing rapidly. It is believed that only important inventions to be filed to EPO, taking into account the cost of patenting at EPO and the importance of Europe as a technology market; thus, collections of Chinese patents at the EPO should contain important inventions. Second, the database updates its data every six months and it contains a significant number of variables that are useful in tracking innovation activities of the patentees, includes forward citations, backward citations, technology fields, and sectors of applicants, to name just a few.

The data contain joint patents that owned by two Chinese applicants: one company applicant (main applicant) and one university applicant (co-applicant). I focus on joint patents that display firm as the main applicant because the interest of the chapter is analysing firm as the major entity of innovation. Joint patents developed by three or more applicants are excluded from the sample, as multiple partnerships make interpretation complex[9]. There are a total of 1115 joint patents for the period 1985-2010.

7.4.2 Measures

Table 7.1 presents the summary statistics for the sample. Table 7.2 shows the correlation matrix for all variables; the table reveals that there is strong correlation between most variables.

[9] For example, if company co-patent with a university and a research organisation at the same time, it is difficult to separate the contributions made by partners.

Table 7. 1 Descriptive statistics

Variable	Obs	Min	Max	Mean	Std. Dev.	Variance	Skewness	Kurtosis
Forward citations	1,116	0	15	0.58	1.52	2.3	4.22	25.61
Organisational proximity	1,116	0	1	0.49	0.5	0.25	0.04	1
Cognitive proximity	1,116	0	1	0.18	0.33	0.11	1.73	4.37
Firm’s absorptive ability	1,116	1	12,936	3,196.72	3,967.18	1.57e+07	0.94	2.65
Patent scope	1,116	1	8	2.06	1.19	1.42	1.64	7.27
Inventors	1,116	0	24	6.34	3.91	15.32	1.07	3.83
Backward citations	1,116	0	94	3.27	4.84	23.45	7.93	124.26
NPL citations	1,116	0	84	1.32	4.35	18.94	12.26	203.59
Patent claims	1,116	0	48	3.02	8.05	64.84	4.75	40.53
Patent family size	1,116	1	20	5.52	3.25	10.54	1.11	4.75
Technology field dummy								
Chemical patent	260*	0	1					
Mechanical engineering patent	280*	0	1					
Electrical engineering patent	530*	0	1					
Instruments patent	46*	0	1					

Note: entries with an asterisk (*) denote the number of 1s in the underlying dummy variable.

Table 7. 2 Pearson’s correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Forward citations	1										
(2) Organisational proximity	0.0607*	1									
(3) Cognitive proximity	-0.0114	0.4348*	1								
(4) Cognitive proximity squared	-0.0135	0.4100*	0.9761*	1							
(5) Firm’s absorptive ability	-0.0276	0.1536*	-0.3255*	-0.2567*	1						
(6) Patent scope	0.0955*	-0.0217	-0.0188	-0.0296	-0.1158*	1					
(7) Inventors	0.0812*	0.3870*	0.2327*	0.2655*	0.1946*	-0.1074*	1				
(8) Backward citations	0.2912*	0.0114	-0.0377	-0.0322	-0.0160	0.0014	-0.0096	1			
(9) NPL citations	0.0595*	-0.2149*	-0.1384*	-0.1360*	-0.0340	0.1892*	-0.1614*	0.1222*	1		
(10) Patent family size	0.0334	0.2933	0.0852*	0.0737*	0.0695*	0.1824*	0.2597*	-0.0805*	-0.0176	1	
(11) Patent claims	0.2551*	-0.0416	0.0242	0.0317	0.0314	0.1529*	-0.0445	0.1334*	0.2406*	0.1287*	1

7.4.2.1 Dependent variable

Patent citations are effective measures of knowledge flows (Crescenzi et al., 2016), innovation value (e.g. Phene et al., 2006; Singh, 2008), because they contain richer information and cover wider aspects than R&D expenditures (Trajtenberg's, 1990). Hall et al (2005) measured the stock market evaluation of firms using patent citations and found that patent citations are significantly and positively associated with market value of the firms.

I measure the value of joint patent as the number of forward citations received by joint patent within five years of the publication date. Since there is usually a lag between the application and the publication/granting date, newer inventions may be less likely to be cited due to lack of exposure. This is a widespread problem in many studies that used patent citations as measure of value of innovation. Following the study of Hall et al. (2001), I truncate the dataset so that every patent has an equal five-year period to be cited. This should address the problem.

7.4.2.2 Independent variables

Cognitive proximity. As suggested by previous studies, cognitive proximity is the extent to which partners share "the same knowledge base and expertise" (Boschma, 2005, pp. 63). Following the definition, I use the ratio of jointly developed patents in a firm's patent portfolio as the measure of cognitive proximity between firm and university. Specifically, the variable is obtained by taking the number of jointly developed patents between a firm and a university over the number of patents owned by a firm. This measure is expected to capture a firm's experience in collaborating with the academia. Thus, the higher the ratio, the more experienced a firm in academic collaboration. I expect that this variable would have an inverted-U shape impact on the value of innovation. In other words, a certain level of cognitive proximity is expected to be beneficial to the value creation of an innovation, however too much cognitive proximity will lead to an opposite result.

Organisational proximity. The variable indicates that if the firm is a spin-off or a former spin-off of the university. The variable takes the value 1 if the firm is a spin-off, and 0 if otherwise. The data on organizational proximity was extracted from company and university websites and was double-checked by the authors. The intuition here is that the existence of organizational ties can facilitate collaboration by bringing the knowledge and resources of different units of the organisaiton together that is more difficult to achieve in external collaborations, hence organizational proximity is likely to have a positive impact on value of innovation.

In line with the standard literature on patent-level regression analysis, I include the following control variables that might influence the patent's value: patent scope, number of inventors, number of backward citations, number of NPL citations, size of patent family and number of patent claims. Definition of these variables are covered in Chapter 3. In addition, I believe that the ratio of joint patents with university is subject to a firm's absorptive ability. In the econometric model, I measure absorptive ability as the number of patents.

7.4.3 Econometric analysis

7.4.3.1. The model

The econometric model is specified as follows:

$$\text{Citations}_i = \beta_0 + \beta_1\text{OrganisationalProximity}_i + \beta_2\text{CognitiveProximity}_i + \beta_3\text{AbsorptiveAbility}_i + \beta_4\text{Backward}_i + \beta_5\text{PatentScope}_i + \beta_6\text{Inventors}_i + \beta_7\text{Technologies}_i + \beta_8\text{NPL}_i + \epsilon_i$$

where Citations_i denotes the number of forward citations received within five years of patent publication; $\text{OrganisationalProximity}_i$ and CognitiveProximity are the independent variables; FirmExperience is captured by a firm's patent portfolio; Technologies_i represents the number of technology fields captured by the patent. Inventors_i refers to the number of inventors worked for a given invention. LnBackward_i denotes the number of patent literature cited by a given invention. $LnNPL_i$ refers to the number of scientific literature included in a given patent application. $PatentScope_i$ defines the technological breadth of the patent application.

7.4.3.2 Econometric method

Citations received by patents are classic example of a discrete probability distribution, which gives the probability of a few independent events occurring in a fixed time. In the example of my data, every citation received by a joint patent is an independent event and is non-negative integer. Count models provide a better fit than classic linear regression models (such as OLS). In this chapter, a range of count models are employed: PQGPMLE (benchmark model), NB1 (main model), and NB2 (robustness checks). These models are covered in Chapter 3.

7.5 Results

This section presents the benchmark results before discusses the main results, and concludes by reporting the robustness test. For the reason of comparison, both model effects and marginal effects are presented here. Nevertheless, when it comes to interpretation of results, marginal effects are the focus. I look at the AME, which first aggregates all individual responses and then calculates the average response.

7.5.1 Benchmark results

Table 7.3 reports the benchmark model effects as well as benchmark marginal effects for the PQGPMLE.

Table 7. 3 Benchmark model effects and marginal effects of PQGPMLE

	I	II	III	IV	V	VI
		Model effects			Marginal effects	
Organisational proximity	-0.032		0.034	-0.045		0.043
	(0.199)		(0.199)	(0.279)		(0.248)
Cognitive proximity		1.299	1.236		1.615	1.545
		(1.191)	(1.146)		(1.548)	(1.492)
Cognitive proximity ^2		-1.809	-1.764		-2.250	-2.205
		(1.202)	(1.157)		(1.611)	(1.566)
Absorptive ability	-0.060**	-0.067**	-0.069**	-0.084	-0.084*	-0.086*
	(0.027)	(0.030)	(0.031)	(0.054)	(0.046)	(0.049)
Patent scope	0.051	0.060	0.059	0.072	0.074	0.073
	(0.070)	(0.068)	(0.069)	(0.095)	(0.083)	(0.084)
Inventors	0.042*	0.051**	0.050**	0.058	0.063*	0.063*
	(0.023)	(0.024)	(0.024)	(0.041)	(0.035)	(0.035)
Backward citations	0.918***	0.914***	0.913***	1.285**	1.137***	1.142***
	(0.092)	(0.087)	(0.089)	(0.503)	(0.345)	(0.351)
NPL citations	-0.231*	-0.241**	-0.240**	-0.323	-0.300	-0.300
	(0.120)	(0.117)	(0.118)	(0.234)	(0.192)	(0.192)
Patent family size	-0.142	-0.168	-0.173	-0.198	-0.209	-0.216
	(0.135)	(0.134)	(0.138)	(0.216)	(0.184)	(0.193)
Patent claims	0.064***	0.064***	0.064***	0.090*	0.080**	0.080**
	(0.010)	(0.010)	(0.010)	(0.050)	(0.036)	(0.037)
Chemical patent	0.131	0.127	0.128	0.168	0.142	0.144
	(0.192)	(0.194)	(0.193)	(0.262)	(0.226)	(0.227)
Mechanical engineering patent	0.476**	0.503**	0.490**	0.732	0.688*	0.671*
	(0.239)	(0.229)	(0.244)	(0.468)	(0.383)	(0.391)
Electrical engineering patent	0.087	0.067	0.066	0.109	0.073	0.072
	(0.196)	(0.206)	(0.207)	(0.251)	(0.225)	(0.228)
Instrument patent	0.023	0.050	0.049	0.028	0.054	0.053
	(0.368)	(0.362)	(0.365)	(0.451)	(0.398)	(0.404)
Observations	1,116	1,116	1,116			
df	13	13	13			
Loglikelihood	-953.2	-953.2	-953.2			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Coefficients of organisational proximity variable (Column II – III, V – VI) are insignificant although negative. Results of the model and marginal effects are consistent. As shown by the model effects (Columns II – III), cognitive proximity has a moderate inverted U-shaped effect on forward citations received, other factors being constant. Initially, cognitive proximity is found to be positive and statistically significant on forward citations. Then, the squared form of cognitive proximity is shown to be negative and statistically significant on forward citations. It is noted that the effect of reduction in forward citations is stronger compared with the effect of gain in forward citations.

Since marginal effects are typically non-linear functions of all the estimated parameters and independent variables, the marginal effect associated with a particular coefficient does not necessarily shows the same sign or significance as shown in the model. Results of the marginal effects show that cognitive proximity is positively associated with forward citations; squared cognitive proximity is negatively associated with forward citations. In practical terms, cognitive proximity is found to increase forward citations by between 2.6 to 2.7 units, then decrease forward citations by between 3 to 3.1 units.

As far as the control variables are concerned, the model effects (Columns I – III) show that the effect of patent scope and inventors are positive but statistically insignificant on forward citations. The effect of the size of patent family is negative and statistically insignificant on forward citations. The coefficient of absorptive ability is negative and statistically significant, while the coefficient of backward citation is found to be positive and statistically significant on forward citations. As indicated by the marginal effects (Columns IV – VI), a firm’s absorptive ability marginally decreases forward citations by 0.1 citation. Backward citations are shown to increase forward citations by 1.1 units. NPL citations are found to decrease forward citations by 0.3 units. Number of patent claims is found to increase forward citations by less than 0.1 unit.

7.5.2 Main results and discussion

Table 7.4 reports the main results for the NB1. As shown by the model effects (Columns I – III), the coefficient of organisational proximity is insignificant although positive. The marginal effects (Columns IV – VI) show that the coefficient of organisational proximity is insignificant although negative. As previously explained, since marginal effects are typically non-linear functions of all the estimated parameters and independent variables, there is no guarantee that the marginal effect associated with a particular coefficient shows the same sign or significance as shown in the model.

The finding that organizational proximity is insignificantly associated with patent quality links to the ongoing debate on the effect of organizational proximity on innovation performance in the existing literature. Scholars who stand on the positive side of the debate (e.g. Capaldo, A. and Petruzzelli, 2014) believe that organizational proximity can reduce uncertainty and opportunism in the course of new knowledge creation by offering strong control mechanisms, such as protecting ownership rights and ensuring sufficient rewards. Furthermore, knowledge collaboration within firms might be more efficient because they are more likely to focus on the area that they already know (Van Wijk et al., 2008).

Scholars with different opinions argue that organizational proximity is dependent on relation-based communication and understanding, leading to a tendency to look inward (e.g. Boschma, 2005; Capaldo and Petruzzelli, 2014), hence hurts a firm’s ability to innovate. Since partners from the same organisation tend to look for technologies that are already in the portfolio of the neighbourhoods, further learning and innovation is obscured (Nelson and Winter, 2009, Stuart and Podolny, 1996). It is also believed that organizational hierarchy is not efficient in terms of responding to changes and it typically lacks the flexibility to manage innovative ideas (Lundvall and Nielson, 2007).

Table 7. 4 Main model effects and marginal effects for of NB1

	I	II	III	IV	V	VI
		Model effects			Marginal effects	
Organisational proximity	0.083		0.096	-0.065		0.024
	(0.144)		(0.157)	(0.124)		(0.138)
Cognitive proximity		1.365	1.177		0.209	0.164
		(0.862)	(0.905)		(0.744)	(0.788)
Cognitive proximity ^2		-1.616*	-1.475		-0.568	-0.534
		(0.898)	(0.919)		(0.785)	(0.807)
Absorptive ability	-0.044**	-0.041*	-0.045*	-0.052***	-0.063***	-0.064***
	(0.022)	(0.024)	(0.024)	(0.018)	(0.019)	(0.019)
Patent scope	0.059	0.069	0.064	0.117**	0.117***	0.115***
	(0.052)	(0.050)	(0.052)	(0.047)	(0.044)	(0.044)
Inventors	0.019	0.031	0.030	0.022	0.031*	0.031*
	(0.019)	(0.020)	(0.020)	(0.017)	(0.018)	(0.018)
Backward citations	0.692***	0.695***	0.694***	0.729***	0.728***	0.728***
	(0.077)	(0.076)	(0.076)	(0.093)	(0.091)	(0.091)
NPL citations	-0.070	-0.083	-0.077	-0.031	-0.041	-0.039
	(0.089)	(0.088)	(0.090)	(0.073)	(0.071)	(0.073)
Patent family size	0.071	0.059	0.048	-0.091	-0.108	-0.111
	(0.118)	(0.115)	(0.118)	(0.098)	(0.096)	(0.098)
Patent claims	0.027***	0.029***	0.029***	0.028***	0.031***	0.031***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Chemical patent	-1.112***	-1.149***	-1.152***	-0.945***	-0.921***	-0.924***
	(0.172)	(0.178)	(0.178)	(0.228)	(0.221)	(0.224)
Mechanical engineering patent	-0.852***	-0.833***	-0.864***	-0.563**	-0.520*	-0.532*
	(0.204)	(0.206)	(0.209)	(0.285)	(0.273)	(0.281)
Electrical engineering patent	-1.101***	-1.137***	-1.140***	-1.006***	-0.994***	-0.998***
	(0.164)	(0.170)	(0.169)	(0.237)	(0.228)	(0.230)
Instrument patent	-1.497***	-1.477***	-1.491***	-1.072***	-1.041***	-1.046***
	(0.362)	(0.356)	(0.359)	(0.306)	(0.293)	(0.297)
Observations	1,116	1,116	1,116			

df	13	13	13
Loglikelihood	-953.2	-953.2	-953.2

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns I – III (model effects) show that the coefficient of cognitive proximity is positive and statistically significant ($p<0.05$); the coefficient of squared cognitive proximity is negative and statistically significant ($p<0.05$). Columns IV – VI (marginal effects) show that while the coefficient of cognitive proximity is positive, the coefficient of squared cognitive proximity is negative. In practical terms, the variable is found to increase forward citation by between 1 to 1.1 units, then decrease forward citations by between 1.1 to 1.3 units.

The results suggest that sharing some technological similarity with universities weakly benefits the collaboration up to a certain point, then gradually diminish. The finding resonates with that of Petruzzelli (2011), who empirically demonstrates the curvilinear relationship between technological relatedness and the value of joint invention. For the purposes of capturing the opportunities created by collaboration and accumulate knowledge (Steinmo and Rasmussen, 2016) and reducing the cost associated with knowledge searching (Perez and Soete, 1988), greater technological relatedness with the innovation partner appears to be beneficial. However, cognitive proximity is a sword that has two sides. On the one hand, it can facilitate collaborations by converging different capabilities to desired goals. On the other hand, it can encourage inward looking and limit partner's ability as to 'think outside of box'.

The inverted-U shape suggests, that a certain degree of knowledge diversification is required for absorbing new knowledge efficiently (Petruzzelli, 2011; Steinmo and Rasmussen, 2016). In other words, a certain level of cognitive distance needs to be maintained to be able to transfer more complex knowledge. When partner's knowledge bases are too similar, the creation of new technologies and rising of market opportunities will be restrained (Knoben and Oelremans, 2006). In addition, a certain degree of technological distance is also a critical condition to form R&D collaborations, because it provides opportunities for partners to get access to new knowledge and capabilities.

As far as the control variables are concerned, the model effects of them are largely consistent with those reported by the benchmark model (Table 7.3). The coefficient of backward citation is positive and statistically significant ($p<0.01$), suggesting that backward citation is a strong indicator for forward citations. The coefficient of patent claim is positive and statistically significant ($p<0.01$), though the effect is smaller compared with backward citation. The coefficient of absorptive ability is negative and weakly significant. The coefficients of remaining variables are insignificant. When it comes to marginal effects, the coefficients of patent scope, backward citations, and patent claims are positive and statistically significant, whereas the coefficient of absorptive ability is negatively associated with forward citations. In practical terms, a firm's absorptive ability (as measured by firm's patent portfolio) decreases forward citation by 0.1 unit. patent scope is shown to increase forward citations by 0.1 unit; backward citation is found to increase forward citations by 0.7 units; patent claim is shown to increase forward citations by less than 0.1 unit.

7.5.3 Robustness test

To test the robustness of main results, I employ the NB2. Table 7.5 shows the results for NB2.

The consistent outcome is cognitive proximity has an inverted U-shaped effect on the number of forward citations received (Columns I – III). Specifically, the coefficient of cognitive proximity is positive and statistically significant ($p<0.05$); the coefficient of squared cognitive proximity is negative and statistically significant ($p<0.05$). The coefficient of organisational proximity is insignificant, which is also consistent with the finding of main results.

As far as the control variables are concerned, the robustness test shows that the model effects of all the control variables are consistent with those reported by the benchmark and main model effects.

Table 7. 5 Robustness model effects and marginal effects of NB2

	I	II	III	IV	V	VI
		Model effects			Marginal effects	
Organisational proximity	0.065		0.100	0.162		0.195
	(0.209)		(0.208)	(0.563)		(0.438)
Cognitive proximity		1.546	1.341		2.978	2.676
		(1.274)	(1.224)		(3.137)	(3.000)
Cognitive proximity ^2		-1.958	-1.807		-3.772	-3.607
		(1.286)	(1.234)		(3.434)	(3.385)
Absorptive ability	-0.077***	-0.076**	-0.081**	-0.196	-0.147	-0.161
	(0.028)	(0.031)	(0.033)	(0.186)	(0.112)	(0.131)
Patent scope	0.033	0.042	0.040	0.084	0.082	0.079
	(0.068)	(0.066)	(0.067)	(0.171)	(0.127)	(0.132)
Inventors	0.036	0.044*	0.043*	0.092	0.086	0.086
	(0.024)	(0.024)	(0.024)	(0.094)	(0.069)	(0.072)
Backward citations	0.940***	0.942***	0.941***	2.393	1.815	1.877
	(0.092)	(0.088)	(0.088)	(1.893)	(1.108)	(1.203)
NPL citations	-0.209*	-0.225*	-0.226**	-0.533	-0.433	-0.451
	(0.120)	(0.116)	(0.115)	(0.546)	(0.374)	(0.395)
Patent family size	-0.119	-0.135	-0.149	-0.303	-0.261	-0.298
	(0.130)	(0.131)	(0.133)	(0.441)	(0.309)	(0.347)
Patent claims	0.076***	0.075***	0.075***	0.192	0.144	0.150
	(0.012)	(0.011)	(0.011)	(0.184)	(0.110)	(0.120)
Chemical patent	0.163	0.146	0.152	0.424	0.275	0.299
	(0.201)	(0.205)	(0.206)	(0.646)	(0.428)	(0.457)
Mechanical engineering patent	0.374	0.441*	0.405	1.082	0.973	0.912
	(0.267)	(0.251)	(0.267)	(1.100)	(0.822)	(0.814)
Electrical engineering patent	0.048	0.040	0.037	0.116	0.071	0.070
	(0.207)	(0.213)	(0.213)	(0.504)	(0.381)	(0.396)
Instrument patent	-0.007	0.006	0.009	-0.018	0.011	0.016
	(0.372)	(0.364)	(0.367)	(0.883)	(0.642)	(0.676)
Observations	1,116	1,116	1,116			
df	13	13	13			
Loglikelihood	-953.2	-953.2	-953.2			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7.6 Chapter summary

This chapter explores how proximity dimensions affect the value of patents jointly owned by firms and universities in China. The findings show that cognitive proximity has a positive impact on the value creation of joint patents, however when the level of cognitive proximity reaches a certain point, the positive impact on value creation diminishes. This suggests that too much cognitive proximity between collaboration partners could harm the value of joint inventions. I did not find empirical support for the hypothesis that organizational proximity has a positive impact on the value of joint patents. In fact, organizational proximity is found insignificantly related to the value of joint patents.

This chapter has a few implications to research and practice. To practitioners, what they can take away from this study is a lesson on the trade-off between knowledge proximity and knowledge diversity. While knowledge proximity is important for collaboration success, it is also important to be aware of role of knowledge diversity in shaping the economic value of joint inventions. For better learning and interaction purposes, firms should select university partners that have a certain level of knowledge overlapping in the technology in development.

To alleviate the negative impact brought by knowledge proximity, some degree of knowledge diversity and the ability to absorb such knowledge are critical. It appears that this is an important trade-off to firms, since searching for partners with more heterogeneous knowledge suggests high costs and less efficiency in integrating the new knowledge, while focusing on exploitation of knowledge that already know means that the economic value of such innovation may be low.

For increasing the value of innovation, it emerges that collaboration within the same organisation may not be a sensible choice. One possible explanation is that cognitive dimension that is embedded in organizational proximity. Collaboration within the same organisation suggests that partners share similar knowledge bases and organizational cultures.

These similarities may be at the expense of knowledge diversity, which is important for generating valuable inventions.

To research, this study adds value to current research on the impact of proximity dimensions on value creation. To those who are interested in the relationship between proximity and innovation performance, this study provides strong empirical support for the inverted U-shaped effect of cognitive proximity on innovation performance and highlights the fact that too much organizational proximity may not improve innovation performance.

To those who are interested in the relationship between knowledge similarities and knowledge diversity, this study reminds that, while a certain level of knowledge similarities is required for smooth coordination and knowledge integration, some degree of knowledge diversity is also important for innovative performance.

To those are interested in the industry-university relations in China, my study provides an empirical analysis that looks at the history, current situation, and effectiveness of industry-university collaborations.

Chapter 8 Conclusion

Evidence from joint patenting can reflect the trend in R&D linkages in a nation's innovation system. In this thesis, joint patent is used as an important window for examining the development and transformations within China's NIS. The aim of this thesis is to unfold the trends and patterns of R&D collaborations in China, as well as to help improve current understanding on the performance of these collaborations. Better insights into collaboration strategies and their effects on innovation performance would allow the formulation of an open technology policy.

Drawing upon joint patent data from the European Patent Office, this thesis empirically addresses the following research objectives in empirical chapters. In the first empirical chapter, the research objective is to analyse and compare the effects of university and cross-border co-ownerships, as well as organisational proximity on joint patent quality, which is measured by the number of forward citations received within five years.

The empirical findings confirm the positive effects of university and cross-border co-ownerships on joint patent quality. First, my finding is consistent with that of Beers et al. (2014) that the geographical diversity of partners positively influences innovation performance of firms. Second, the findings that international university collaboration is positively associated with joint patenting performance supports the claim that university knowledge spillovers resulting from research collaboration can occur over longer geographical distances (Ponds et al., 2009). Finally, the influence of internal collaboration (i.e. organisational proximity) on joint patent quality, is ambiguous.

Drawing upon a larger sample that covers joint patent observations for 80 countries, an objective of the second empirical chapter is to explore the effect of cross-border co-ownership on joint patent quality. Compared with the previous chapter, cross-border collaboration is further divided into eight groups using World Bank's country classifications[10]. The empirical finding suggests that cross-border co-ownership is a strong indicator for joint patent quality, confirming the finding of Briggs (2015).

Another objective of this chapter is to investigate the effect of university co-ownership on joint patent quality. Compared with the previous chapter, this chapter further divides university collaboration into domestic and international collaboration based on geographical proximity[11]. The empirical finding shows that domestic university collaboration is conductive to high quality patent, supporting the argument of Qiu et al. (2017). This finding contrasts with that of the previous chapter, which reports that international university collaboration is conducive to high patent performance. Differences in results is likely to be contingent on contexts. While Chapter 1 focuses exclusively on China, Chapter 2 includes data on 80 countries.

The third empirical chapter analyses the effects of proximity dimensions on joint patent quality. The first objective is to explore whether sharing similar knowledge bases (cognitive proximity) is conductive to high quality patent. The empirical finding confirms the inverted U-shaped effect of cognitive proximity on joint patent quality, resonating with the study of Petruzzelli (2011) that a moderate level of organisational proximity is beneficial to collaborative performance.

The second objective is to investigate whether collaboration (organizational proximity) between different units of the same organization is conductive to high quality patent. The empirical evidence does not find support for the role of organisational proximity in enhancing joint patent quality. Possible explanations include partners from the same organisation tend to look for technologies that are already in the portfolio of the neighbourhoods (Nelson and Winter, 2009;

[10] The World Bank assigns a country to one of the following categories: (1) low-income country; (2) lower-middle income country; (3) upper-middle income country; (4) high-income country.

[11] In this chapter, university collaboration is divided into domestic university collaboration and international university collaboration

Stuart and Podolny, 1996); organizational hierarchy is inefficient in responding to changes and it typically lacks the flexibility to manage innovative ideas (Lundvall and Nielson, 2007).

The last empirical chapter analyses the propensity of collaborating with universities, as well as compares the effects of industrial research and university research on joint patent quality. Specifically, the first objective is to explore the relationship between the level of technology sector and the propensity to enter research partnership with universities. The empirical evidence shows that firms in high-technology sectors are more likely to collaborate with universities, resonating with the finding of Zhou's (2012).

The second objective is to compare the quality of joint patents emerged from industrial research and university research. The empirical results show that the roles of industrial research and university research are complementary in generating technological innovations in China: while industrial research is conductive to high quality inventions for medium and high technology sectors, university research is conductive to high quality inventions for medium and low technology sectors.

The thesis is among the first attempts to analyse the factors affecting the quality of joint patents in China. At a higher level, this piece of research contributes to the growing body of literature on open innovation, which treats R&D as an open process. The open innovation paradigm assumes that firms should combine internal ideas as well as external ideas in its innovation activities. Since patent collaboration involves use of external ideas, joint patent is a reliable indicator of open innovation. Therefore, findings from this research provide insights for managing open innovation of a particular type.

At a lower level, this piece of research contributes to the overall understanding of R&D collaboration in China, including collaboration strategies (i.e. co-ownerships), and collaboration performance (i.e. joint patent quality). Knowing strategies and their effects on collaboration provides insights into the formulation and implementation of innovation policies in the emerging country. The empirical evidence from this research agrees with the argument that collaboration with key innovators is one way to enhance the quality of innovation.

An important question may raise from this research is that to what extent can joint patenting can be seen as evidence of true collaboration. Although joint patents represent output of important R&D projects, they may not capture all the collaborative activities by firms. Therefore, a limitation of this thesis is that the findings may not be applied to all collaborative activities. Future research is needed to study why some collaborative activities do not yield a joint patent.

Due to the difficulty of accessing firm-level financial data, in particular small firms, the empirical studies did not investigate the impact of firm-level characteristics on joint patent performance. It would be fruitful to explore how firm characteristics influence joint patent performance, by matching firm-level data with patent level data. For example, possible research questions could be: 1) What are the firm-level determinants of joint patent performance? 2) Does R&D expenditure of the firm affect joint patent performance?

With the access to firm-level financial data, future research could link industry-level data with firm-level data to examine the effect of industrial dynamics on the propensity to co-patent. For instance, researchers could look at the effect of industrial FDI on firm's propensity to co-patent. This question is important for the Chinese government to design policies that promote R&D linkages between main innovators in the country. Future research could also study whether productivity affect the propensity to co-patent. This question can be useful for firm managers to allocate resources for improving productivity.

Since there is no known database recording university-industry interaction in China, the empirical analysis was unable to control for, for example, university's experience in managing industrial R&D. Future research should include such control variables in the empirical analysis.

An important caveat concerning endogeneity needs to be issued. In this thesis, endogeneity can arise from two possible sources. First, this can be due to selection bias. Firms that collaborate are usually already more innovative than those do not. Second, endogeneity can be due to matching. Firms' collaboration behaviour and patenting outcome could be jointly driven by unobserved characteristics, such as strategic objectives.

List of References

Acosta, M., Coronado, D. and Martínez, M.Á., 2012. Spatial differences in the quality of university patenting: Do regions matter? *Research Policy*, *41*(4), pp.692-703.

Acs, Z.J., Braunerhjelm, P., Audretsch, D.B. and Carlsson, B., 2009. The knowledge spillover theory of entrepreneurship. *Small business economics, 32*(1), pp.15-30.

Adams, P., Fontana, R. and Malerba, F., 2013. The magnitude of innovation by demand in a sectoral system: The role of industrial users in semiconductors. *Research Policy, 42*(1), pp.1-14.

Agapitova, N., 2005, June. The role of social networks for National Innovation Systems' dynamics. In *DRUID 10th Anniversary Summer Conference* (pp. 27-29).

Agrawal, A., Kapur, D. and McHale, J., 2008. How do spatial and social proximity influence knowledge flows? Evidence from patent data. *Journal of urban economics, 64*(2), pp.258-269.

Almeida, P., Song, J., Grant, R.M., 2002. Are Firms Superior to Alliances and Markets? An Empirical Test of Cross Border Knowledge Building. *Organization Science 13*(2), 147-161.

Anselin, L., Varga, A. and Acs, Z., 2000. Geographical spillovers and university research: A spatial econometricperspective. *Growth and change*, *31*(4), pp.501-515.

Archibugi, D., Coco, A., 2004. International partnerships for knowledge in business and academia. A comparison between Europe and the USA. *Technovation 24*(7), 517-528.

Arora, A. and Gambardella, A., 1990. Complementarity and external linkages: the strategies of the large firms in biotechnology. *The Journal of Industrial Economics*, pp.361-379.

Arza, V., 2010. Channels, benefits and risks of public—private interactions for knowledge transfer: conceptual framework inspired by Latin America. *Science and Public Policy*, *37*(7), pp.473-484.

Audretsch, D.B., 1997. Technological regimes, industrial demography and the evolution of industrial structures. *Industrial and corporate change, 6*(1), pp.49-82.

Audretsch, D., Lehmann, E. and Warning, S., 2004. University spillovers: Does the kind of science matter?. *Industry and innovation*, *11*(3), pp.193-206.

Autant-Bernard, C., Mairesse, J. and Massard, N., 2007. Spatial knowledge diffusion through collaborative networks. *Papers in Regional Science*, *86*(3), pp.341-350.

Baba, Y., Shichijo, N., & Sedita, S. R. (2009). How do collaborations with universities affect firms' innovative performance? The role of "Pasteur scientists" in the advanced materials field. *Research Policy, 38*(5), 756-764.

Badir, Y.F. and O'Connor, G.C., 2015. The formation of tie strength in a strategic alliance's first new product development project: The influence of project and partners' characteristics. *Journal of Product Innovation Management*, *32*(1), pp.154-169.

Balland, P.A., Boschma, R. and Frenken, K., 2015. Proximity and innovation: From statics to dynamics. *Regional Studies*, *49*(6), pp.907-920.

Barberá-Tomás, D., Jiménez-Sáez, F. and Castelló-Molina, I., 2011. Mapping the importance of the real world: The validity of connectivity analysis of patent citations networks. *Research Policy*, *40*(3), pp.473-486.

Barney, J., 1991. Firm resources and sustained competitive advantage. *Journal of management*, *17*(1), pp.99-120.

Beck, M., Lopes-Bento, C. and Schenker-Wicki, A., 2016. Radical or incremental: Where does R&D policy hit?. *Research Policy*, *45*(4), pp.869-883.

Becker, W. and Dietz, J., 2004. R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry. *Research policy, 33*(2), pp.209-223.

Beers, C. and Zand, F., 2014. R&D cooperation, partner diversity, and innovation performance: an empirical analysis. *Journal of Product Innovation Management, 31*(2), pp.292-312.

Belderbos, R., Carree, M. and Lokshin, B., 2006. Complementarity in R&D cooperation strategies. *Review of Industrial Organization*, *28*(4), pp.401-426.

Belderbos, R., Cassiman, B., Faems, D., Leten, B. and Van Looy, B., 2014. Co-ownership of intellectual property: Exploring the value-appropriation and value-creation implications of co-patenting with different partners. *Research Policy, 43*(5), pp.841-852.

Bergek, A. and Bruzelius, M., 2010. Are patents with multiple inventors from different countries a good indicator of international R&D collaboration? The case of ABB. *Research Policy, 39*(10), pp.1321-1334.

Belderbos, R., Faems, D., Leten, B. and Looy, B.V., 2010. Technological activities and their impact on the financial performance of the firm: Exploitation and exploration within and between firms. *Journal of Product Innovation Management*, *27*(6), pp.869-882.

Bernstein, S., 2015. Does going public affect innovation?. *The Journal of Finance*, *70*(4), pp.1365-1403.

Blind, K., Cremers, K. and Mueller, E., 2009. The influence of strategic patenting on companies' patent portfolios. *Research Policy*, *38*(2), pp.428-436.

Boeing, P., Mueller, E. and Sandner, P., 2016. China's R&D explosion—Analyzing productivity effects across ownership types and over time. *Research Policy, 45*(1), pp.159-176.

Bonaccorsi, A. and Thoma, G., 2007. Institutional complementarity and inventive performance in nano science and technology. *Research Policy*, *36*(6), pp.813-831.

Bonaccorsi, A. and Lipparini, A., 1994. Strategic partnerships in new product development: an Italian case study. *Journal of product innovation management*, *11*(2), pp.134-145.

Boschma, R., 2005. Proximity and innovation: a critical assessment. *Regional studies, 39*(1), pp.61-74.

Branstetter, L., Li, G. and Veloso, F., 2014. The Rise of International Coinvention. In *The Changing Frontier: Rethinking Science and Innovation Policy* (pp. 135-168). University of Chicago Press.

Briggs, K., 2015. Co-owner relationships conducive to high quality joint patents. *Research Policy, 44(*8), pp.1566-1573.

Broekel, T. and Boschma, R., 2011. Knowledge networks in the Dutch aviation industry: the proximity paradox. *Journal of Economic Geography*, *12*(2), pp.409-433.

Burgers, W.P., Hill, C.W. and Kim, W.C., 1993. A theory of global strategic alliances: The case of the global auto industry. *Strategic management journal*, *14*(6), pp.419-432.

Capaldo, A. and Petruzzelli, A.M., 2014. Partner Geographic and Organizational Proximity and the Innovative Performance of Knowledge-Creating Alliances. *European Management Review, 11*(1), pp.63-84.

Carbonara, N. and Giannoccaro, I., 2011. Interpreting the role of proximity on Industrial District competitiveness using a complexity science-based view and Systems Dynamics simulation. *Journal of geographical systems, 13*(4), pp.415-436.

Castellani, D. and Pieri, F., 2013. R&D offshoring and the productivity growth of European regions. *Research Policy*, *42*(9), pp.1581-1594.

Cassi, L. and Plunket, A., 2015. Research collaboration in co-inventor networks: combining closure, bridging and proximities. *Regional Studies*, *49*(6), pp.936-954.

Chai, S. and Shih, W., 2016. Bridging science and technology through academic–industry partnerships. *Research Policy*, *45*(1), pp.148-158.

Chen, K. and Kenney, M., 2007. Universities/research institutes and regional innovation systems: the cases of Beijing and Shenzhen. *World development, 35*(6), pp.1056-1074.

Chen, J.H., Jang, S.L. and Chang, C.H., 2013. The patterns and propensity for international co-invention: the case of China. *Scientometrics*, *94*(2), pp.481-495.

Chesbrough, H.W., 2006. Open innovation: The new imperative for creating and profiting from technology. Harvard Business Press.

China Daily, 2005. *Overseas Investment on the up*, 1st February.

China Daily, 2017. *European Patent Office notes highest increase in patent applications from China*. [pdf]. Available at:<http://www.chinadaily.com.cn/business/tech/2017-03/08/content_28473143.htm> [Accessed 10th September 2017]

Chou, T.L., Ching, C.H., Fan, S.M. and Chang, J.Y., 2011. Global linkages, the Chinese high-tech community and industrial cluster development: the semiconductor industry in Wuxi, Jingsu. *Urban Studies*, *48*(14), pp.3019-3042.

Cohen, W.M. and Levinthal, D.A., 1989. Innovation and learning: the two faces of R & D. *The Economic Journal, 99*(397), pp.569-596.

Cohen, W.M. and Levinthal, D.A., 2000. Absorptive capacity: A new perspective on learning and innovation. In *Strategic Learning in a Knowledge economy* (pp. 39-67).

Colombo, M.G., Grilli, L. and Piva, E., 2006. In search of complementary assets: The determinants of alliance formation of high-tech start-ups. *Research Policy, 35*(8), pp.1166-1199.

Community and Industrial Cluster Development: The Semiconductor Industry in Wuxi, Jingsu. *Urban Studies, 48*(14), pp.3019-3042.

Contractor, F.J. and Lorange, P., 1988. Cooperative Strategies. *International Business*.

Crescenzi, R., Nathan, M. and Rodríguez-Pose, A., 2016. Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy, 45*(1), pp.177-194.

Das, T.K. and Teng, B.S., 2000. A resource-based theory of strategic alliances. *Journal of management*, *26*(1), pp.31-61.

De Faria, P., Lima, F. and Santos, R., 2010. Cooperation in innovation activities: The importance of partners. *Research Policy, 39*(8), pp.1082-1092.

De Jong, J.P. and Freel, M., 2010. Absorptive capacity and the reach of collaboration in high technology small firms. *Research Policy*, *39*(1), pp.47-54.

De Rassenfosse, G., Dernis, H., Guellec, D., Picci, L. and de la Potterie, B.V.P., 2013. The worldwide count of priority patents: A new indicator of inventive activity. *Research Policy*, *42*(3), pp.720-737.

Dornbusch, F. and Neuhäusler, P., 2015. Composition of inventor teams and technological progress–The role of collaboration between academia and industry. *Research Policy, 44*(7), pp.1360-1375.

Doz, Y.L., 1996. The evolution of cooperation in strategic alliances: Initial conditions or learning processes? *Strategic Management Journal*, *17*(S1), pp.55-83.

Etzkowitz, H., Webster, A., 1998. Entrepreneurial science: the second academic revolution. In: Etzkowitz, H., Webster, A., Healey, P. (Eds.), 1998. Capitalizing Knowledge:

New Intersections of Industry and Academia. State University of New York Press, Albany, pp. 21–46.

Etzkowitz, H., 2002. MIT and the Rise of Entrepreneurial Science. Routledge, London.

Etzkowitz, H. and Leydesdorff, L., 2000. The dynamics of innovation: from National Systems and “Mode 2” to a Triple Helix of university–industry–government relations. *Research policy*, *29*(2), pp.109-123.

Eun, J.H., Lee, K. and Wu, G., 2006. Explaining the “University-run enterprises” in China: A theoretical framework for university–industry relationship in developing countries and its application to China. *Research Policy*, *35*(9), pp.1329-1346.

Fagerberg, J., 1994. Technology and international differences in growth rates. *Journal of economic Literature*, *32*(3), pp.1147-1175.

Feldman, M. P. (1994a). The Geography of Innovation (Kluwer Academic Publishers, Boston).

Feldman, M. (1994b), “Knowledge complementarity and innovation, *Small Business Economics 6*(3): 363-372.

Feldman, M.P. and Kelley, M.R., 2006. The ex-ante assessment of knowledge spillovers: Government R&D policy, economic incentives and private firm behavior. *Research Policy*, *35*(10), pp.1509-1521.

Fischer, T. and Leidinger, J., 2014. Testing patent value indicators on directly observed patent value—An empirical analysis of Ocean Tomo patent auctions. *Research Policy*, *43*(3), pp.519-529.

Fontana, R., Geuna, A. and Matt, M., 2006. Factors affecting university–industry R&D projects: The importance of searching, screening and signalling. *Research Policy, 35*(2), pp.309-323.

Freddi, D., 2009. The integration of old and new technological paradigms in low-and medium-tech sectors: The case of mechatronics. *Research Policy, 38*(3), pp.548-558.

Frost, T.S., Zhou, C., 2005. R&D co-practice and ‘reverse’ knowledge integration in multinational firms. *Journal of International Business Studies 36*(6), 676-687.

Funk, M., 2013. Patent sharing by US universities: an examination of university joint patenting. *Economics of Innovation and New Technology*, *22*(4), pp.373-391.

Furman, J.L. and Stern, S., 2011. Climbing atop the shoulders of giants: The impact of institutions on cumulative research. *The American Economic Review*, *101*(5), pp.1933-1963.

García-Manjón, J.V. and Romero-Merino, M.E., 2012. Research, development, and firm growth. Empirical evidence from European top R&D spending firms. *Research Policy*, *41*(6), pp.1084-1092.

Geroski, P.A., 1992. Vertical relations between firms and industrial policy. *The Economic Journal*, *102*(410), pp.138-147.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G. and van den Oord, A., 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. *Research policy*, *37*(10), pp.1717-1731.

Giuliani, E., Martinelli, A. and Rabellotti, R., 2016. Is co-invention expediting technological catch up? A study of collaboration between emerging country firms and EU inventors. *World Development*, *77*, pp.192-205.

Gittelman, M., 2006. National institutions, public–private knowledge flows, and innovation performance: A comparative study of the biotechnology industry in the US and France. *Research Policy*, *35*(7), pp.1052-1068.

Glaeser, E., H. Kallal, J. Scheinkman, and A.. Shleifer (1992), Growth of cities," *Journal of Political Economy 100*: 1126-1152.

Glaister, K.W., 1998. Strategic Motives for UK International Alliance Formation. In *International Strategic Management and Government Policy.* (pp. 40-77). Palgrave Macmillan UK.

Gnyawali, D.R. and Park, B.J.R., 2011. Co-opetition between giants: Collaboration with competitors for technological innovation. *Research Policy*, *40*(5), pp.650-663.

Grimpe, C. and Sofka, W., 2009. Search patterns and absorptive capacity: Low-and high-technology sectors in European countries. *Research policy, 38*(3), pp.495-506.

Grossman, G.M. and Helpman, E., 1993. *Innovation and growth in the global economy*. MIT press.

Guan, J. and Chen, Z., 2012. Patent collaboration and international knowledge flow. *Information Processing & Management*, *48*(1), pp.170-181.

Guan, J. and Yam, R.C., 2015. Effects of government financial incentives on firms' innovation performance in China: Evidences from Beijing in the 1990s. *Research Policy*, *44*(1), pp.273-282.

Guan, J.C., Yam, R.C. and Mok, C.K., 2005. Collaboration between industry and research institutes/universities on industrial innovation in Beijing, China. *Technology Analysis & Strategic Management*, *17*(3), pp.339-353.

Guellec, D. and de la Potterie, B.V.P., 2001. The internationalisation of technology analysed with patent data. *Research Policy*, *30*(8), pp.1253-1266.

Hagedoorn, J., 2003. Sharing intellectual property rights—an exploratory study of joint patenting amongst companies. *Industrial and Corporate Change*, *12*(5), pp.1035-1050.

Hagedoorn, J., Kranenburg, H.V. and Osborn, R.N., 2003. Joint patenting amongst companies–exploring the effects of inter-firm R&D partnering and experience. *Managerial and Decision Economics*, *24*(2-3), pp.71-84.

Hall, B.H., Jaffe, A.B. and Trajtenberg, M., 2000. *Market value and patent citations: A first look* (No. w7741). national bureau of economic research.

Hall, B.H., Jaffe, A.B. and Trajtenberg, M., 2001. *The NBER patent citation data file: Lessons, insights and methodological tools* (No. w8498). National Bureau of Economic Research.

Hall, B.H., Jaffe, A. and Trajtenberg, M., 2005. Market value and patent citations. *RAND Journal of economics*, pp.16-38.

Hansen, M.T., 1999. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative science quarterly, 44*(1), pp.82-111.

Hansen, P.A. and Serin, G., 1997. Will low technology products disappear? The hidden innovation processes in low technology industries. *Technological Forecasting and Social Change, 55*(2), pp.179-191.

Henderson, R., Jaffe, A.B. and Trajtenberg, M., 1998. Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. *The review of economics and statistics*, *80*(1), pp.119-127.

Hausman, J.A., Hall, B.H. and Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship.

Harhoff, D., Narin, F., Scherer, F.M. and Vopel, K., 1999. Citation frequency and the value of patented inventions. *The review of Economics and Statistics*, *81*(3), pp.511-515.

Harhoff, D., Scherer, F.M. and Vopel, K., 2003. Citations, family size, opposition and the value of patent rights. *Research policy*, *32*(8), pp.1343-1363.

Harrigan, K.R., 1985. Vertical integration and corporate strategy. *Academy of Management journal*, *28*(2), pp.397-425.

Harrigan, K.R., 1986. *Managing for joint venture success*. Simon and Schuster.

Harrigan, K.R., 1988. Joint ventures and competitive strategy. *Strategic Management Journal*, *9*(2), pp.141-158.

Hatzichronoglou, T., 1997. Revision of the high-technology sector and product classification.
Hausman, J.A., Hall, B.H. and Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship.

Hemmert, M. (2004). The influence of institutional factors on the technology acquisition performance of high-tech firms: survey results from Germany and Japan. *Research Policy, 33*(6), 1019-1039.

Hewitt-Dundas, N., 2006. Resource and capability constraints to innovation in small and large plants. *Small Business Economics*, *26*(3), pp.257-277.

Hicks, D., 2000. 360 Degree linkage analysis. *Research Evaluation*, *9*(2), pp.133-143.

Hoang, H. and Rothaermel, F.T., 2005. The effect of general and partner-specific alliance experience on joint R&D project performance. *Academy of Management Journal, 48*(2), pp.332-345.

Hong, W. and Su, Y.S., 2013. The effect of institutional proximity in non-local university–industry collaborations: An analysis based on Chinese patent data. *Research Policy*, *42*(2), pp.454-464.

Howells, J.R., 2002. Tacit knowledge, innovation and economic geography. *Urban studies*, *39*(5-6), pp.871-884.

Hu, M.C. and Mathews, J.A., 2005. National innovative capacity in East Asia. *Research Policy*, *34*(9), pp.1322-1349.

Hu, M.C. and Mathews, J.A., 2008. China's national innovative capacity. *Research policy*, *37*(9), pp.1465-1479.

Hu, Y., McNamara, P. and Piaskowska, D., 2017. Project Suspensions and Failures in New Product Development: Returns for Entrepreneurial Firms in Co-Development Alliances. *Journal of Product Innovation Management*, *34*(1), pp.35-59.

Jaffe, A.B., and M. Trajtenberg (2002), Patents, citations, and innovations: a window on the knowledge economy, (MIT Press: Cambridge).

Jaffe, A.B., M. Trajtenberg and R. Henderson (1993), Geographic localization of knowledge spillovers as evidenced by patent citations, *Quarterly Journal of Economics 63*: 577- 598.

Johannessen, J.A. and Olsen, B., 2010. The future of value creation and innovations: Aspects of a theory of value creation and innovation in a global knowledge economy. *International Journal of Information Management, 30*(6), pp.502-511.

Kabo, F.W., Cotton-Nessler, N., Hwang, Y., Levenstein, M.C. and Owen-Smith, J., 2014. Proximity effects on the dynamics and outcomes of scientific collaborations. *Research Policy, 43*(9), pp.1469-1485.

Kang, M., Wu, X., Hong, P. and Park, Y., 2012. Aligning organizational control practices with competitive outsourcing performance. *Journal of Business Research*, *65*(8), pp.1195-1201.

Katz, J., 1994. Geographical proximity and scientific collaboration. *Scientometrics, 31*(1), pp.31-43.

Kirat, T. and Lung, Y., 1999. Innovation and proximity territories as loci of collective learning processes. *European urban and regional studies, 6*(1), pp.27-38.

Katila, R. and Mang, P.Y., 2003. Exploiting technological opportunities: the timing of collaborations. *Research policy, 32*(2), pp.317-332.

Kessler, E.H. and Chakrabarti, A.K., 1996. Innovation speed: A conceptual model of context, antecedents, and outcomes. *Academy of Management Review*, *21*(4), pp.1143-1191.

Kim, L., 1997. *Immitation to Innovation; the Dynamics of Korea's Technological Learning*. Harvard Business School Press.

Kim, C. and Song, J., 2007. Creating new technology through alliances: An empirical investigation of joint patents. *Technovation*, *27*(8), pp.461-470.

Kirner, E., Kinkel, S. and Jaeger, A., 2009. Innovation paths and the innovation performance of low-technology firms—An empirical analysis of German industry. *Research Policy, 38*(3), pp.447-458.

Kitanovic, J., 2007. The applicability of the concept of national innovation systems to transition economies. *Innovation*, *9*(1), pp.28-45.

Knoben, J. and Oerlemans, L.A., 2006. Proximity and inter-organizational collaboration: A literature review. *International Journal of Management Reviews, 8*(2), pp.71-89.

Kodama, T., 2008. The role of intermediation and absorptive capacity in facilitating university–industry linkages—An empirical study of TAMA in Japan. *Research Policy, 37*(8), pp.1224-1240.

Kogut, B., 1988. Joint ventures: Theoretical and empirical perspectives. *Strategic management journal*, *9*(4), pp.319-332.

KPMG, 2013. Innovated in China: New frontier for global R&D. [pdf] KPMG. Available at: http://www.kpmg.com/DE/de/Documents/China-360-Issue11-201308-new-frontier-for-global-R-and-D-2013-KPMG.pdf [Accessed 01/08/2016].

Lane, P.J. and Lubatkin, M., 1998. Relative absorptive capacity and interorganizational learning. *Strategic management journal, 19*(5), pp.461-477.

Lanjouw, J.O. and Schankerman, M., 1999. *The quality of ideas: measuring innovation with multiple indicator*s (No. w7345). National bureau of economic research.

Laursen, K. and Salter, A., 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. *Strategic management journal, 27*(2), pp.131-150.

Lawson, C. and Lorenz, E., 1999. Collective learning, tacit knowledge and regional innovative capacity. *Regional studies, 33*(4), pp.305-317.

Ledwith, A. and Coughlan, P., 2005. Splendid isolation: does networking really increase new product success? *Creativity and Innovation Management, 14*(4), pp.366-373.

Lee, K., 2005. Making a Technological Catch-up: Barriers and opportunities. *Asian Journal of Technology Innovation*, *13*(2), pp.97-131.

Lee, Y.S., 1996. 'Technology transfer'and the research university: a search for the boundaries of university-industry collaboration. *Research policy, 25*(6), pp.843-863.

Lee, Y. and Cavusgil, S.T., 2006. Enhancing alliance performance: The effects of contractual-based versus relational-based governance. *Journal of business research, 59*(8), pp.896-905.

Lei, X.P., Zhao, Z.Y., Zhang, X., Chen, D.Z., Huang, M.H. and Zhao, Y.H., 2011. The inventive activities and collaboration pattern of university–industry–government in China based on patent analysis. *Scientometrics, 90*(1), pp.231-251.

Leiponen, A. and Helfat, C.E., 2010. Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal, 31*(2), pp.224-236.

Lerner, J., 1994. The importance of patent scope: an empirical analysis. *The RAND Journal of Economics*, pp.319-333.

Levitt B. and March J., 1996. Organizational learning, in Cohen M. D. and Sproull L. S. (Eds) *Organizational Learning*, pp. 516–541. Thousand Oaks, CA, Sage.

Lhuillery, S., & Pfister, E. (2009). R&D cooperation and failures in innovation projects: Empirical evidence from French CIS data. *Research Policy, 38*(1), 45-57.

Li, X., 2012. Behind the recent surge of Chinese patenting: An institutional view. *Research Policy, 41(*1), pp.236-249.

Liang, L. and Zhu, L., 2002. Major factors affecting China's inter-regional research collaboration: Regional scientific productivity and geographical proximity. *Scientometrics*, *55*(2), pp.287-316.

Lin, C., Wu, Y.J., Chang, C., Wang, W. and Lee, C.Y., 2012. The alliance innovation performance of R&D alliances—the absorptive capacity perspective. *Technovation*, *32*(5), pp.282-292.

Linder, S.B., 1961. *An essay on trade and transformation*. Wiley.

Link, A.N., Paton, D. and Siegel, D.S., 2002. An analysis of policy initiatives to promote strategic research partnerships. *Research Policy, 31*(8), pp.1459-1466.

Lissoni, F., Mairesse, J., Montobbio, F. and Pezzoni, M., 2011. Scientific productivity and academic promotion: a study on French and Italian physicists. *Industrial and corporate change*, *20*(1), pp.253-294.

Liu, X. and Buck, T., 2007. Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries. *Research policy, 36*(3), pp.355-366.

Liu, X. and White, S., 2001. Comparing innovation systems: a framework and application to China's transitional context. *Research policy*, *30*(7), pp.1091-1114.

Lo, S. S., 2010. Scientific linkage of science research and technology development: A case of genetic engineering research. *Scientometrics, 82*(1), pp.109-120.

Lööf, H., 2009. Multinational enterprises and innovation: firm level evidence on spillover via R&D collaboration. *Journal of Evolutionary Economics 19*(1), 41-71.

Love, J.H., Roper, S. and Vahter, P., 2014. Learning from openness: The dynamics of breadth in external innovation linkages. *Strategic management journal, 35*(11), pp.1703-1716.

Lundvall, B.Å. and Nielsen, P., 2007. Knowledge management and innovation performance. *International Journal of Manpower*,*28*(3/4), pp.207-223.

Luo, Y., 2007. Are joint venture partners more opportunistic in a more volatile environment?. *Strategic Management Journal*, *28*(1), pp.39-60.

M'Chirgui, Z., 2009. Dynamics of R&D networked relationships and mergers and acquisitions in the smart card field. *Research Policy, 38*(9), pp.1453-1467.

Maggioni, M.A., Nosvelli, M. and Uberti, T.E., 2007. Space versus networks in the geography of innovation: A European analysis. *Papers in Regional Science*, *86*(3), pp.471-493.

Maietta, O.W., 2015. Determinants of university–firm R&D collaboration and its impact on innovation: A perspective from a low-tech industry. *Research Policy, 44*(7), pp.1341-1359.

Malmberg, A. and Maskell, P., 2002. The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering. *Environment and planning A*, *34*(3), pp.429-449.

March, J.G., 1991. Exploration and exploitation in organizational learning. *Organization science, 2*(1), pp.71-87.

Martínez, C., 2010. Patent families: when do different definitions really matter?. *Scientometrics*, *86*(1), pp.39-63.

Miller, D. J., Fern, M. J., & Cardinal, L. B. (2007). The use of knowledge for technological innovation within diversified firms. *Academy of Management Journal, 50*(2), 307-325.

Monge, P.R., Rothman, L.W., Eisenberg, E.M., Miller, K.I. and Kirste, K.K., 1985. The dynamics of organizational proximity. *Management Science, 31*(9), pp.1129-1141.

Monjon, S., & Waelbroeck, P. (2003). Assessing spillovers from universities to firms: evidence from French firm-level data. *International Journal of Industrial Organization, 21*(9), 1255-1270.

Montobbio, F. and Sterzi, V., 2013. The globalization of technology in emerging markets: a gravity model on the determinants of international patent collaborations. *World Development*, *44*, pp.281-299.

Mowery, D.C., 2005. The Bayh-Dole act and high-technology entrepreneurship in US universities: Chicken, egg, or something else? In *University entrepreneurship and technology transfer* (pp. 39-68). Emerald Group Publishing Limited.

Nadiri, M.I., 1993. *Innovations and technological spillovers* (No. w4423). National Bureau of Economic Research.

Nakamura, M., 2003. Research alliances and collaborations: introduction to the special issue. *Managerial and Decision Economics*, *24*(2/3), pp.47-49.

Narula, R., 2004. R&D collaboration by SMEs: new opportunities and limitations in the face of globalisation. *Technovation*, *24*(2), pp.153-161.

Natalicchio, A., Natalicchio, A., Messeni Petruzzelli, A., Messeni Petruzzelli, A., Garavelli, A.C. and Garavelli, A.C., 2017. The impact of partners' technological diversification in joint patenting: A study on firm-PRO collaborations. *Management Decision*, *55*(6), pp.1248-1264.

Nature Index China tables, 2015. Nature Index. [online] Available at: <http://www.nature.com/nature/journal/v528/n7582_supp_ni/fig_tab/528S191a_T1.html > [Accessed 02/03/2016].

Naughton, B., 1997. Danwei: The Economic Foundations of a Unique Institution. In: Lu, X.B., Perry, E.J. (Eds.), *Danwei: The Changing Chinese Workplace in Historical and Comparative Perspective*. M.E.Sharpe, Armonk, pp. 169–194.

Nelson, R.R., 1982. *Government and Technical Progress: a cross-industry analysis*. Pergamon.

Nelson, R.R. and Winter, S.G., 2009. *An evolutionary theory of economic change*. Harvard University Press.

Nemet, G.F. and Johnson, E., 2012. Do important inventions benefit from knowledge originating in other technological domains?. *Research Policy*, *41*(1), pp.190-200.

Neuhäusler, P. and Frietsch, R., 2013. Patent families as macro level patent value indicators: applying weights to account for market differences. *Scientometrics*, *96*(1), pp.27-49.

Nooteboom, B., 2000. *Learning and innovation in organizations and economies*. OUP Oxford.

Oerlemans, L. and Meeus, M., 2005. Do organizational and spatial proximity impact on firm performance?. *Regional studies*, *39*(1), pp.89-104.

Park, H.W. and Leydesdorff, L., 2010. Longitudinal trends in networks of university–industry–government relations in South Korea: The role of programmatic incentives. *Research policy*, *39*(5), pp.640-649.

Patel, P. and Pavitt, K., 1991. Large firms in the production of the world's technology: an important case of" non-globalisation". *Journal of international business studies*, pp.1-21.

Pavitt, K., 1984. Sectoral patterns of technical change: towards a taxonomy and a theory. Research policy, 13(6), pp.343-373.

Perez C. and Soete L., 1988. Catching up in technology: entry barriers and windows, in Dosi G., Freeman C., Nelson R., Silverberg G. and Soete L. (Eds) Technical Change and Economic Theory, pp. 458-479. Pinter, London.

Peri, G., 2004. Knowledge flows and productivity. *Rivista di Politica Economica, 94*(2), pp.21-59.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D'Este, P. & Sobrero, M. (2013). Academic engagement and commercialisation: A review of the literature on university–industry relations. *Research Policy, 42*(2), 423-442.

Petruzzelli, A.M., 2011. The impact of technological relatedness, prior ties, and geographical distance on university–industry collaborations: A joint-patent analysis. *Technovation, 31*(7), pp.309-319.

Picci, L., 2010. The internationalization of inventive activity: A gravity model using patent data. *Research Policy*, *39*(8), pp.1070-1081.

Phene, A., Fladmoe-Lindquist, K. and Marsh, L., 2006. Breakthrough innovations in the US biotechnology industry: the effects of technological space and geographic origin. *Strategic Management Journal, 27*(4), pp.369-388.

Pisano, G.P., 1990. The R&D boundaries of the firm: an empirical analysis. *Administrative Science Quarterly*, pp.153-176.

Pisano, G.P., Bohmer, R.M. and Edmondson, A.C., 2001. Organizational differences in rates of learning: Evidence from the adoption of minimally invasive cardiac surgery. *Management Science, 47*(6), pp.752-768.

Pisano, G.P. and Teece, D.J., 2007. How to capture value from innovation: Shaping intellectual property and industry architecture. *California Management Review, 50*(1), pp.278-296.

Ponds, R., Oort, F.V. and Frenken, K., 2009. Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, *10*(2), pp.231-255.

Porter, M.E., 1998. Cluster and the new economics of competition. *Harvard Business Review, 76*(6), pp.77-90.

Qiu, S., Liu, X. and Gao, T., 2017. Do emerging countries prefer local knowledge or distant knowledge? Spillover effect of university collaborations on local firms. *Research Policy, 46*(7), pp.1299-1311.

Qu, Z., Huang, C., Zhang, M. and Zhao, Y., 2013. R&D offshoring, technology learning and R&D efforts of host country firms in emerging economies. *Research Policy*, *42*(2), pp.502-516.

Roberts, E.B., 1991. *Entrepreneurs in high technology: Lessons from MIT and beyond*. Oxford University Press.

Rodríguez G., 2016. *Poisson Models for Count Data*, [online] Available at: <http://data.princeton.edu/wws509/notes/c4.pdf> [Accessed 10/03/2016].

Romanelli, E. and Khessina, O.M., 2005. Regional industrial identity: Cluster configurations and economic development. *Organization Science, 16*(4), pp.344-358.

Roijakkers, N. and Hagedoorn, J., 2006. Inter-firm R&D partnering in pharmaceutical biotechnology since 1975: Trends, patterns, and networks. *Research Policy, 35*(3), pp.431-446.

Roijakkers, N., Hagedoorn, J. and van Kranenburg, H., 2005. Dual market structures and the likelihood of repeated ties–evidence from pharmaceutical biotechnology. *Research Policy, 34*(2), pp.235-245.

Rothaermel, F.T., 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*, *22*(6-7), pp.687-699.

Sage Publishing, 2016. *Generalized linear models*, [online] Available at: <http://www.sagepub.com/sites/default/files/upm-binaries/21121_Chapter_15.pdf> [Accessed 10/03/2016].

Sakakibara, M., 1997. Heterogeneity of firm capabilities and cooperative research and development: an empirical examination of motives. *Strategic management journal*, pp.143-164.

Sampat, B.N. and Ziedonis, A.A., 2002. Cite seeing: Patent citations and the economic value of patents. Unpublished manuscript, from the author.

Sampson, R. C. (2007). R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. Academy of Management Journal, 50(2), 364-386.

Saxton, T., 1997. The effects of partner and relationship characteristics on alliance outcomes. *Academy of management journal, 40*(2), pp.443-461.

Scandura, A., 2016. University–industry collaboration and firms' R&D effort. *Research Policy*, *45*(9), pp.1907-1922.

Schaaper, M., 2009. Measuring China's innovation system: National specificities and international comparisons. *OECD Science, Technology and Industry Working Papers*, *2009*(1), p.0_1.

Schartinger, D., Rammer, C., Fischer, M.M. and Fröhlich, J., 2002. Knowledge interactions between universities and industry in Austria: sectoral patterns and determinants. *Research policy, 31*(3), pp.303-328.

Schmoch, U., Laville, F., Patel, P. and Frietsch, R., 2003. Linking technology areas to industrial sectors. *Final Report to the European Commission, DG Research*, *1*(0), p.100.

Santamaría, L., Barge-Gil, A. and Modrego, A., 2010. Public selection and financing of R&D cooperative projects: Credit versus subsidy funding. *Research Policy*, *39*(4), pp.549-563.

Santamaría, L., Nieto, M.J. and Barge-Gil, A., 2009. Beyond formal R&D: Taking advantage of other sources of innovation in low-and medium-technology industries. Research Policy, 38(3), pp.507-517.

Siegel, D.S., Westhead, P. and Wright, M., 2003. Science parks and the performance of new technology-based firms: a review of recent UK evidence and an agenda for future research. *Small Business Economics*, *20*(2), pp.177-184.

Siliverstovs, B. and Kancs, A., 2016. R&D and non-linear productivity growth. *Research Policy, 45*(3), pp.634-646.

Singh, J., 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy, 37*(1), pp.77-96.

Spithoven, A. and Teirlinck, P., 2015. Internal capabilities, network resources and appropriation mechanisms as determinants of R&D outsourcing. *Research Policy*, *44*(3), pp.711-725.

Steinmo, M. and Rasmussen, E., 2016. How firms collaborate with public research organizations: The evolution of proximity dimensions in successful innovation projects. *Journal of Business Research, 69*(3), pp.1250-1259.

Sterzi, V., 2013. Patent quality and ownership: An analysis of UK faculty patenting. *Research Policy, 42*(2), pp.564-576.

Stuart, T.E. and Podolny, J.M., 1996. Local search and the evolution of technological capabilities. *Strategic Management Journal, 17*(S1), pp.21-38.

Stuart, T.E., Ozdemir, S.Z. and Ding, W.W., 2007. Vertical alliance networks: The case of university–biotechnology–pharmaceutical alliance chains. *Research Policy, 36*(4), pp.477-498.

Teece, D.J., 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy, 15*(6), pp.285-305.

Teng, B.S., 2007. Managing intellectual property in R&D alliances. *International Journal of Technology Management*, *38*(1-2), pp.160-177.

Tether, B.S., 2002. Who co-operates for innovation, and why: an empirical analysis. *Research policy, 31*(6), pp.947-967.

Thomas, P. and Breitzman, A., 2006. A method for identifying hot patents and linking them to government-funded scientific research. *Research Evaluation*, *15*(2), pp.145-152.

Thursby, J., Fuller, A.W. and Thursby, M., 2009. US faculty patenting: Inside and outside the university. *Research Policy, 38*(1), pp.14-25.

Tinbergen, J., 1962. Shaping the world economy; suggestions for an international economic policy. *Books (Jan Tinbergen)*.

Tong, X., & Frame, J. D. (1994). Measuring national technological performance with patent claims data. *Research Policy, 23*(2), 133-141.

Torre, A. and Rallet, A., 2005. Proximity and localization. *Regional studies*, *39*(1), pp.47-59.

Torrisi, S., Gambardella, A., Giuri, P., Harhoff, D., Hoisl, K. and Mariani, M., 2016. Used, blocking and sleeping patents: Empirical evidence from a large-scale inventor survey. *Research Policy*, *45*(7), pp.1374-1385.

Tsang, E. W. 1998. Can guanxi be a source of sustained competitive advantage for doing business in China?. *The Academy of Management Executive, 12*(2), 64-73.

Tsai, K.H. and Wang, J.C., 2009. External technology sourcing and innovation performance in LMT sectors: An analysis based on the Taiwanese Technological Innovation Survey. *Research Policy, 38*(3), pp.518-526.

Tsang, E.W., 1999. A preliminary typology of learning in international strategic alliances. *Journal of World Business*, *34*(3), pp.211-229.

Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, pp.172-187.

Van Wijk, R., Jansen, J.J. and Lyles, M.A., 2008. Inter-and intra-organizational knowledge transfer: a meta-analytic review and assessment of its antecedents and consequences*. Journal of Management Studies, 45*(4), pp.830-853.

Wang, S.J., 2007. Factors to evaluate a patent in addition to citations. *Scientometrics*, *71*(3), pp.509-522.Wijnberg, N.M., 1994. National systems of innovation: Selection environments and selection processes. *Technology in Society*, *16*(3), pp.313-320.

Wernerfelt, B., 1984. A resource-based view of the firm. *Strategic management journal*, *5*(2), pp.171-180.

World Bank, 2017. World Bank Country and Lending Groups. World Bank. Available at: <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups> [Accessed 12/08/2017].

Wu, J., 2012. Technological collaboration in product innovation: The role of market competition and sectoral technological intensity. *Research Policy, 41*(2), pp.489-496.

Wu, J. and Shanley, M.T., 2009. Knowledge stock, exploration, and innovation: Research on the United States electromedical device industry. *Journal of business research, 62*(4), pp.474-483.

Wuyts, S., Colombo, M.G., Dutta, S. and Nooteboom, B., 2005. Empirical tests of optimal cognitive distance. *Journal of Economic Behavior & Organization, 58*(2), pp.277-302.

Xue, L., 2004. University-market linkages in China: The case of university-affiliated enterprises. In *symposium on University, Research Institute and Industry Relations in the US, Taiwan and Mainland China, Stanford Project on Regions of Innovation and Entrepreneurship, Palo Alto, CA*.

Yu, J. and Nijkamp, P., 2009. Ownership, R&D and Productivity Change: Assessing the Catch-up in China's High-tech Industries. *Studies in Regional Science, 39*(1), pp.149-173.

Zhang, J. and Baden-Fuller, C., 2010. The influence of technological knowledge base and organizational structure on technology collaboration. *Journal of Management Studies*, *47*(4), pp.679-704.

Zheng, J., Zhao, Z.Y., Zhang, X., Chen, D.Z., Huang, M.H., Lei, X.P., Zhang, Z.Y. and Zhao, Y.H., 2012. International scientific and technological collaboration of China from 2004 to 2008: a perspective from paper and patent analysis. *Scientometrics*, *91*(1), pp.65-80.

Zhou, W., 2012. Determinants and effects of research partnerships in China's emerging market. *Contemporary Economic Policy, 30*(1), pp.129-147.

Zukin, S. and DiMaggio, P.J., 1990. *Structure of capital*. Cambridge, UK: Cambridge University Press, 1(3), p.5.

Appendix 1 Test for multicollinearity among variables (Chapter 5)

Variable	**VIF**	**1/VIF**
Organisational proximity	2.31	0.432159
Cross Border	1.7	0.589008
University	2.32	0.431388
Backward	1.27	0.788406
NPL	1.19	0.838267
Inventors	1.41	0.709267
Patent families	1.36	0.736317
Claims	1.2	0.830113
Technologies	1.17	0.854488
WIPO patent field dummies		
Chemical patent	10.1	0.099034
Mechanical engineering patent	4.71	0.21247
Electrical engineering patent	10.79	0.092701
Instrument patent	3.49	0.286482
Mean VIF	3.31	

Appendix 2 Model effects of OLS (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII
University co-ownership			0.388		1.167***		0.604**	1.326***
			(0.264)		(0.320)		(0.254)	(0.306)
Organisational proximity				-0.088		-0.600**	0.299*	0.221
				(0.217)		(0.247)	(0.171)	(0.173)
Cross-border co-ownership		2.963***			3.274***	3.088***		3.270***
		(0.274)			(0.341)	(0.310)		(0.342)
Backward citation	1.474***	1.342***	1.484***	1.478***	1.358***	1.365***	1.475***	1.351***
	(0.100)	(0.095)	(0.101)	(0.101)	(0.096)	(0.097)	(0.101)	(0.096)
NPL citation	-0.403	-0.263	-0.471*	-0.423*	-0.452*	-0.396	-0.439*	-0.429*
	(0.256)	(0.260)	(0.241)	(0.245)	(0.237)	(0.242)	(0.243)	(0.239)
Inventors	-0.090***	0.050**	-0.100***	-0.092***	0.034	0.045**	-0.101***	0.033
	(0.024)	(0.021)	(0.027)	(0.025)	(0.021)	(0.021)	(0.027)	(0.021)
Patent family size	-0.132***	-0.100***	-0.136***	-0.133***	-0.109***	-0.109***	-0.133***	-0.107***
	(0.020)	(0.017)	(0.021)	(0.022)	(0.019)	(0.019)	(0.022)	(0.019)
Patent claim	0.242***	0.229***	0.245***	0.243***	0.233***	0.234***	0.243***	0.232***
	(0.022)	(0.020)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.021)
Technology field	1.047***	1.039***	1.036***	1.046***	1.007***	1.034***	1.032***	1.004***
	(0.189)	(0.184)	(0.187)	(0.188)	(0.181)	(0.184)	(0.187)	(0.181)
Chemical patent	1.308***	0.730*	1.249***	1.316***	0.491	0.759*	1.189***	0.448
	(0.402)	(0.407)	(0.411)	(0.400)	(0.432)	(0.409)	(0.411)	(0.430)
mechanical engineering patent	-0.176	-0.278	-0.345	-0.191	-0.796*	-0.383	-0.388	-0.827**
	(0.386)	(0.383)	(0.400)	(0.386)	(0.411)	(0.390)	(0.400)	(0.410)
electrical engineering patent	-0.513	-0.132	-0.575	-0.511	-0.279	-0.103	-0.616	-0.309
	(0.402)	(0.400)	(0.396)	(0.403)	(0.394)	(0.407)	(0.398)	(0.395)
Instrument patent	-0.547	-0.617	-0.602	-0.543	-0.790*	-0.591	-0.647	-0.823**
	(0.404)	(0.396)	(0.406)	(0.405)	(0.404)	(0.402)	(0.408)	(0.405)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247
R-squared	0.240	0.262	0.240	0.240	0.265	0.263	0.240	0.265

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2 reports the model effects of OLS for Chapter 5.

The effect of cross-border ownership is significant and positive ($p<0.01$) throughout Columns II, V, VI, and VIII, whereas the effect of university ownership is strong and positive in Columns V, VII, and VIII; that is, when cross-border ownership variable or/and organisational proximity variable are added.

The coefficient of organisational proximity is negative and statistically significant ($p<0.01$) when cross-border co-ownership variable is included; it is positive and weakly significant when university co-ownership variable is added.

The effects of the control variables are consistent across all Columns. For instance, the coefficients of backward citations, patent claims, and technology fields are positive and statistically significant ($p<0.01$). The coefficient of size of patent family is negative and statistically significant ($p<0.01$). The results of the effect of the size of invention team is mixed. The strong negative effect changed to positive when cross-border ownership is added as an explanatory variable; the strong negative effect remained unchanged when university ownership is added as an explanatory variable; the strong negative effect ceased when both of explanatory variables are added.

Appendix 3 Model effects of PQMLE (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII
University co-ownership			0.403***		0.565***		0.718***	0.940***
			(0.103)		(0.090)		(0.147)	(0.164)
Organisational proximity				-0.141		-0.246***	0.377***	0.444***
				(0.100)		(0.094)	(0.132)	(0.154)
Cross-border co-ownership		1.267***			1.327***	1.267***		1.365***
		(0.117)			(0.108)	(0.109)		(0.114)
Backward citation	0.685***	0.620***	0.710***	0.698***	0.640***	0.638***	0.697***	0.626***
	(0.038)	(0.037)	(0.038)	(0.039)	(0.036)	(0.037)	(0.039)	(0.036)
NPL citation	0.068	0.078	0.008	0.042	-0.007	0.032	0.027	0.013
	(0.086)	(0.076)	(0.080)	(0.082)	(0.072)	(0.074)	(0.081)	(0.072)
Inventors	-0.033**	0.028**	-0.043***	-0.036**	0.020	0.024*	-0.041***	0.023*
	(0.015)	(0.013)	(0.015)	(0.015)	(0.013)	(0.013)	(0.015)	(0.013)
Patent family size	-0.130***	-0.074***	-0.145***	-0.136***	-0.084***	-0.082***	-0.142***	-0.078***
	(0.019)	(0.015)	(0.021)	(0.020)	(0.016)	(0.015)	(0.021)	(0.015)
Patent claim	0.043***	0.040***	0.044***	0.043***	0.042***	0.040***	0.045***	0.043***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)
Technology field	0.211***	0.181***	0.208***	0.212***	0.175***	0.184***	0.201***	0.166***
	(0.038)	(0.035)	(0.036)	(0.038)	(0.033)	(0.034)	(0.036)	(0.032)
Chemical patent	0.266*	0.176	0.226	0.282*	0.146	0.219	0.168	0.072
	(0.156)	(0.151)	(0.157)	(0.159)	(0.154)	(0.160)	(0.153)	(0.146)
mechanical engineering patent	-0.086	-0.050	-0.215	-0.098	-0.211	-0.059	-0.266	-0.273*
	(0.170)	(0.167)	(0.172)	(0.172)	(0.169)	(0.173)	(0.167)	(0.162)
electrical engineering patent	-0.071	0.252	-0.147	-0.069	0.128	0.243	-0.195	0.088
	(0.188)	(0.192)	(0.179)	(0.189)	(0.180)	(0.193)	(0.177)	(0.174)
Instrument patent	-0.349*	-0.311	-0.404**	-0.341*	-0.368*	-0.288	-0.457**	-0.430**
	(0.198)	(0.193)	(0.202)	(0.201)	(0.198)	(0.200)	(0.199)	(0.192)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 3 reports the model effects of PQMLE for Chapter 5.

It is found that the coefficients of university co-ownership stay positive and significant ($p<0.01$) across all Columns. The coefficients of cross-border co-ownership is positive and statistically significant ($p<0.01$). The coefficients of organisational proximity is positive and statistically significant ($p<0.01$) for Column VII and VIII but negative for Column IV and VI ($p<0.01$).

The effects of the control variables are similar to those obtained by the OLS (Appendix 2).

Appendix 4 Marginal effects of PQGPMLE (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII
University co-ownership			1.592***		2.432***		3.429***	5.211***
			(0.476)		(0.506)		(0.934)	(1.418)
Organisational proximity				-0.464		-0.819**	1.254***	1.533***
				(0.356)		(0.374)	(0.364)	(0.459)
Cross-border co-ownership		3.087***			3.298***	3.078***		3.446***
		(0.368)			(0.349)	(0.346)		(0.362)
Backward citation	2.217***	1.984***	2.314***	2.259***	2.061***	2.031***	2.274***	2.025***
	(0.126)	(0.130)	(0.135)	(0.138)	(0.127)	(0.138)	(0.135)	(0.123)
NPL citation	0.203	0.201	0.005	0.122	-0.065	0.065	0.075	0.017
	(0.266)	(0.253)	(0.246)	(0.251)	(0.229)	(0.246)	(0.246)	(0.227)
Inventors	-0.123***	0.052	-0.157***	-0.134***	0.022	0.036	-0.150***	0.037
	(0.048)	(0.043)	(0.050)	(0.051)	(0.043)	(0.044)	(0.051)	(0.042)
Patent family size	-0.432***	-0.263***	-0.479***	-0.448***	-0.290***	-0.287***	-0.470***	-0.263***
	(0.061)	(0.049)	(0.070)	(0.066)	(0.052)	(0.051)	(0.069)	(0.047)
Patent claim	0.135***	0.131***	0.138***	0.135***	0.134***	0.129***	0.140***	0.139***
	(0.015)	(0.018)	(0.015)	(0.016)	(0.017)	(0.018)	(0.014)	(0.014)
Technology field	0.733***	0.668***	0.732***	0.740***	0.651***	0.675***	0.709***	0.620***
	(0.130)	(0.126)	(0.125)	(0.130)	(0.116)	(0.126)	(0.122)	(0.108)
Chemical patent	1.110**	0.648	1.021**	1.185***	0.569	0.793*	0.761	0.273
	(0.436)	(0.417)	(0.467)	(0.449)	(0.452)	(0.441)	(0.474)	(0.449)
mechanical engineering patent	0.093	0.076	-0.253	0.079	-0.362	0.069	-0.462	-0.589
	(0.459)	(0.446)	(0.482)	(0.463)	(0.469)	(0.458)	(0.485)	(0.463)
electrical engineering patent	-0.143	0.868	-0.341	-0.118	0.481	0.809	-0.539	0.390
	(0.472)	(0.578)	(0.481)	(0.482)	(0.531)	(0.554)	(0.486)	(0.532)
Instrument patent	-0.866*	-0.751*	-1.036**	-0.829*	-0.925*	-0.674	-1.258**	-1.166**
	(0.472)	(0.453)	(0.511)	(0.483)	(0.497)	(0.473)	(0.512)	(0.490)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4 reports the marginal effects of PQGPMLE for Chapter 5.

It shows that the coefficients of university co-ownership are positive and statistically significant ($p<0.01$) across all Columns. In practical terms, university co-ownership is found to increase forward citations by between 1.6 and 5.2 units. The coefficients of cross-border co-ownership is positive and statistically significant ($p<0.01$) across all Columns. In practical terms, cross-border co-ownership is shown to increase forward citations by between 3 and 3.4 units. The coefficients of organisational proximity is positive and statistically significant for Column VII and VIII but negative for Column IV and VI; the role of organisational proximity in increasing forward citations is unclear.

The coefficients of the control variables are consistent across all Columns, and are similar to those reported by the model effects of PQMLE.

Appendix 5 Further analysis of cross-border collaboration.

	I	II
	NB1	NB1
	Model effects	Marginal effects
Intra-firm cross border	0.864***	2.291***
	(0.074)	(0.211)
Inter-firm cross border	0.894***	2.411***
	(0.107)	(0.436)
Organisational proximity	0.391***	1.079***
	(0.114)	(0.295)
University	0.492***	1.779***
	(0.115)	(0.503)
Backward	0.664***	1.998***
	(0.027)	(0.098)
NPL	-0.003	-0.010
	(0.042)	(0.126)
Inventors	0.017*	0.052*
	(0.009)	(0.027)
Patent family size	-0.045***	-0.135***
	(0.010)	(0.030)
Claims	0.037***	0.111***
	(0.004)	(0.013)
Technology field	0.186***	0.561***
	(0.030)	(0.090)
Chemical patent	0.159	0.491
	(0.129)	(0.372)
mechanical engineering patent	-0.130	-0.348
	(0.140)	(0.390)
electrical engineering patent	-0.078	-0.214
	(0.134)	(0.376)
Instrument patent	-0.361**	-0.863**
	(0.151)	(0.388)
Observations	5,247	5,247

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 6 Model effects of PQGPMLE (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII	VIIII
Cross-border*University									0.760***
									(0.160)
University co-ownership			0.196**		0.313***		0.237**	0.300**	0.125
			(0.084)		(0.079)		(0.119)	(0.118)	(0.127)
Cross-border co-ownership		1.049***			1.096***	1.083***		1.097***	0.872***
		(0.085)			(0.088)	(0.087)		(0.088)	(0.095)
Organisational proximity				-0.117		-0.226***	0.054	-0.018	0.076
				(0.076)		(0.075)	(0.105)	(0.110)	(0.108)
Backward citation	0.854***	0.804***	0.857***	0.860***	0.811***	0.817***	0.855***	0.811***	0.827***
	(0.039)	(0.037)	(0.039)	(0.039)	(0.037)	(0.037)	(0.039)	(0.037)	(0.036)
NPL citation	0.032	0.031	0.001	0.007	-0.017	-0.017	0.006	-0.019	-0.012
	(0.072)	(0.066)	(0.072)	(0.073)	(0.066)	(0.067)	(0.073)	(0.067)	(0.068)
Inventors	-0.028**	0.027**	-0.033**	-0.031**	0.022*	0.025**	-0.032**	0.023*	0.026**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Patent family size	-0.073***	-0.042***	-0.074***	-0.074***	-0.043***	-0.044***	-0.074***	-0.044***	-0.047***
	(0.013)	(0.011)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)	(0.011)	(0.011)
Patent claim	0.077***	0.070***	0.078***	0.078***	0.072***	0.073***	0.077***	0.072***	0.072***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Technology field	0.139***	0.116***	0.137***	0.138***	0.111***	0.113***	0.137***	0.111***	0.129***
	(0.039)	(0.036)	(0.038)	(0.039)	(0.034)	(0.035)	(0.038)	(0.034)	(0.034)
Chemical patent	0.447***	0.319**	0.423***	0.452***	0.275*	0.326**	0.416***	0.278*	0.314**
	(0.154)	(0.154)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)	(0.154)
mechanical engineering patent	0.172	0.199	0.081	0.140	0.056	0.143	0.076	0.057	0.126
	(0.175)	(0.176)	(0.175)	(0.174)	(0.176)	(0.175)	(0.176)	(0.177)	(0.177)
electrical engineering patent	0.065	0.236	0.008	0.043	0.164	0.208	0.007	0.165	0.042
	(0.180)	(0.176)	(0.175)	(0.177)	(0.174)	(0.174)	(0.175)	(0.174)	(0.168)
Instrument patent	-0.203	-0.216	-0.233	-0.209	-0.267	-0.228	-0.236	-0.265	-0.268

	(0.182)	(0.179)	(0.182)	(0.182)	(0.180)	(0.179)	(0.182)	(0.180)	(0.180)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 6 reports the model effects of PQGPMLE for Chapter 5.

The coefficients of cross-border co-ownership remains positive and statistically significant ($p<0.01$) across all Columns; in practical terms, cross-border co-ownership is shown to increase forward citations by 1.1 units. The coefficients of university co-ownership are also positive and statistically significant ($p<0.05$); in practical terms, university co-ownership is found to increase forward citation by between 0.2 and 0.3 units. The coefficients of organisational proximity is negative and statistically significant ($p<0.01$) when cross-border co-ownership variable is added (Column VI); in practical terms, organisational proximity between partners is shown to decrease forward citations by about 0.2 units.

The coefficients of the control variables are consistent across all Columns, and are similar to those reported by model effects of OLS and PQMLE.

Appendix 7 Model effects of NB1 (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII	VIIII
					Model effects				
Cross-border*University									0.614***
									(0.114)
University co-ownership			-0.085		0.186***		0.169*	0.446***	0.242**
			(0.059)		(0.062)		(0.098)	(0.105)	(0.117)
Organisational proximity				0.215***		0.049	0.324***	0.326***	0.403***
				(0.059)		(0.067)	(0.095)	(0.103)	(0.116)
Cross-border co-ownership		0.832***			0.888***	0.822***		0.905***	0.673***
		(0.059)			(0.064)	(0.064)		(0.065)	(0.071)
Backward citation	0.693***	0.638***	0.687***	0.673***	0.645***	0.635***	0.675***	0.634***	0.662***
	(0.025)	(0.026)	(0.025)	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.026)
NPL citation	-0.018	0.011	-0.006	0.023	-0.014	0.020	0.019	0.010	-0.001
	(0.038)	(0.039)	(0.039)	(0.039)	(0.040)	(0.040)	(0.039)	(0.039)	(0.042)
Inventors	-0.018**	0.022***	-0.016*	-0.012	0.019**	0.023***	-0.014	0.021**	0.013
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Patent family size	-0.066***	-0.041***	-0.064***	-0.060***	-0.044***	-0.040***	-0.062***	-0.041***	-0.043***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)
Patent claim	0.035***	0.034***	0.035***	0.035***	0.034***	0.034***	0.035***	0.035***	0.037***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Technology field	0.167***	0.167***	0.167***	0.164***	0.167***	0.166***	0.162***	0.162***	0.201***
	(0.028)	(0.028)	(0.028)	(0.027)	(0.028)	(0.028)	(0.027)	(0.027)	(0.029)
Chemical patent	0.383***	0.248**	0.394***	0.358***	0.225*	0.240*	0.326**	0.146	0.183
	(0.137)	(0.126)	(0.138)	(0.138)	(0.127)	(0.126)	(0.140)	(0.127)	(0.130)
mechanical engineering patent	-0.001	-0.033	0.026	0.009	-0.086	-0.034	-0.035	-0.156	-0.107
	(0.150)	(0.140)	(0.151)	(0.150)	(0.141)	(0.140)	(0.152)	(0.140)	(0.142)
electrical engineering patent	-0.187	-0.031	-0.179	-0.216	-0.042	-0.040	-0.243*	-0.101	-0.134
	(0.145)	(0.136)	(0.145)	(0.146)	(0.136)	(0.137)	(0.147)	(0.136)	(0.137)

Instrument patent	-0.218	-0.218	-0.205	-0.235	-0.242	-0.224	-0.266*	-0.308**	-0.358**
	(0.159)	(0.148)	(0.158)	(0.159)	(0.149)	(0.148)	(0.159)	(0.148)	(0.152)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 7 reports the model effects of NB1 for Chapter 5.

Consistent with previous results, the coefficients of cross-border co-ownership are positive and statistically significant (p<0.01) across all Columns; in practical terms, cross-border co-ownership is shown to increase forward citations by between 0.8 and 0.9 units. The coefficients of university co-ownership are positive and statistically significant (p<0.01) for Columns V and VIII; in practical terms, university co-ownership is found to increase forward citation by between 0.2 and 0.4 units. The coefficients of organisational proximity is positive and statistically significant (p<0.01) for Columns IV, VII, and VIII; in practical terms, organisational proximity between partners is shown to increase forward citations by between 0.2 and 0.3 units.

The coefficients of the control variables are consistent across all Columns, and are similar to those reported by model effects of OLS, PQMLE and PQGPMLE.

Appendix 8 Model effects NB2 (Chapter 5)

	I	II	III	IV	V	VI	VII	VIII	VIIII
	Model effects								
Cross-border*University									0.723***
									(0.164)
University co-ownership			0.166**		0.282***		0.167	0.255**	0.108
			(0.084)		(0.080)		(0.120)	(0.119)	(0.127)
Organisational proximity				-0.117		-0.211***	0.001	-0.037	0.054
				(0.076)		(0.075)	(0.107)	(0.111)	(0.108)
Cross-border co-ownership		1.020***			1.064***	1.052***		1.065***	0.868***
		(0.087)			(0.089)	(0.089)		(0.089)	(0.099)
Backward citation	0.891***	0.834***	0.894***	0.897***	0.839***	0.845***	0.894***	0.840***	0.852***
	(0.040)	(0.039)	(0.040)	(0.040)	(0.038)	(0.039)	(0.040)	(0.038)	(0.037)
NPL citation	0.048	0.042	0.023	0.023	0.001	-0.002	0.023	-0.002	0.008
	(0.072)	(0.067)	(0.072)	(0.073)	(0.068)	(0.068)	(0.073)	(0.069)	(0.070)
Inventors	-0.028**	0.025**	-0.032**	-0.030**	0.021	0.023*	-0.032**	0.021	0.024*
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Patent family size	-0.062***	-0.039***	-0.064***	-0.064***	-0.040***	-0.041***	-0.064***	-0.041***	-0.044***
	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.011)	(0.013)	(0.011)	(0.011)
Patent claim	0.080***	0.074***	0.081***	0.081***	0.075***	0.076***	0.081***	0.075***	0.074***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Technology field	0.130***	0.110***	0.129***	0.129***	0.106***	0.107***	0.129***	0.106***	0.118***
	(0.040)	(0.036)	(0.039)	(0.039)	(0.035)	(0.036)	(0.039)	(0.035)	(0.035)
Chemical patent	0.469***	0.330**	0.448***	0.475***	0.287*	0.336**	0.448***	0.292*	0.333**
	(0.164)	(0.162)	(0.164)	(0.164)	(0.164)	(0.163)	(0.165)	(0.164)	(0.163)
mechanical engineering patent	0.194	0.223	0.112	0.161	0.085	0.166	0.112	0.088	0.155
	(0.185)	(0.185)	(0.186)	(0.184)	(0.185)	(0.184)	(0.187)	(0.186)	(0.186)
electrical engineering patent	0.074	0.248	0.025	0.051	0.184	0.224	0.025	0.186	0.073
	(0.187)	(0.182)	(0.183)	(0.184)	(0.181)	(0.181)	(0.183)	(0.182)	(0.177)
Instrument patent	-0.199	-0.213	-0.228	-0.207	-0.265	-0.228	-0.228	-0.263	-0.261

	(0.190)	(0.186)	(0.190)	(0.190)	(0.186)	(0.186)	(0.190)	(0.186)	(0.186)
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 8 reports the model effects of NB1 for Chapter 5.

Consistent with previous results, the effect of cross-border co-ownership is positive and statistically significant (p<0.01) on forward citations; in practical terms, cross-border co-ownership is shown to increase forward citations by about 1 unit. The coefficients of university co-ownership are positive and statistically significant (p<0.01) for Columns III, V and VIII; in practical terms, university co-ownership is found to increase forward citation by between 0.2 and 0.3 units. The coefficients of organisational proximity is negative and statistically significant (p<0.01) for Columns VI, VI, and VIII; in practical terms, organisational proximity between partners is shown to decrease forward citations by approximately 0.2 units.

The coefficients of the control variables are consistent across all Columns, and are similar to those reported by model effects of OLS, PQMLE, PQGPMLE, and NB1.

Appendix 9 List of countries in sample (Chapter 5)

Albania, Algeria, Argentina, Australia, Austria, Belgium, Bosnia and Herzegovina, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Cuba, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Japan, Luxembourg, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nigeria, Norway, Peru, Philippines, Poland, Portugal, Romania, Russia, Serbia, Serbia and Montenegro, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sudan, Sweden, Switzerland, Taiwan, Thailand, Trinidad and Tobago, Turkey, United Arab Emirates, The United Kingdom, United Republic of Ukraine, United States of America, Vietnam, Yugoslavia, Zambia, Zimbabwe.

Appendix 10 Model effects of OLS (Chapter 5)

	I	II	III	IV
Domestic academic collaboration		0.30***		0.30***
		(0.02)		(0.02)
International academic collaboration		0.09**		0.09**
		(0.04)		(0.04)
(I) L-L, L-LM, L-UM			-2.80***	-2.78***
			(0.42)	(0.42)
(II) LM-LM			-2.21***	-2.22***
			(0.14)	(0.14)
(III) LM-UM			-1.82***	-1.80***
			(0.14)	(0.14)
(IV) UM-UM			-1.67***	-1.65***
			(0.14)	(0.14)
(V) L-H			-1.75***	-1.75***
			(0.20)	(0.20)
(VI) LM-H			-1.74***	-1.73***
			(0.12)	(0.12)
(VII) UM-H			-1.90***	-1.89***
			(0.10)	(0.10)
(VIII) H-H			-1.62***	-1.60***
			(0.08)	(0.08)
LnIncome	-0.03***	-0.03***	0.07***	0.07***
	(0.00)	(0.00)	(0.01)	(0.01)
LnPatent	0.04***	0.04***	0.10***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)
LnBackward	0.92***	0.94***	0.92***	0.94***
	(0.01)	(0.01)	(0.01)	(0.01)
LnNPL	0.29***	0.26***	0.29***	0.26***
	(0.01)	(0.01)	(0.01)	(0.01)
Inventors	0.07***	0.07***	0.07***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)
FamilySize	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Claims	0.10***	0.10***	0.10***	0.10***
	(0.00)	(0.00)	(0.00)	(0.00)
PatentScope	0.02***	0.02**	0.02***	0.01**
	(0.01)	(0.01)	(0.01)	(0.01)
Time dummies	included	included	included	included
Observations	898,326	898,326	898,326	898,326
R-squared	0.14	0.14	0.14	0.14
df	36	36	36	36

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 10 reports the model effects of OLS for Chapter 5.

Both coefficients of domestic and international university collaborations are positive and statistically significant ($p<0.01$).

It emerges that coefficients of type II (LM-LM), III (LM-UM), and IV (UM-UM) collaborations are negative and statistically significant ($p<0.01$), suggesting that these types of collaborations are negatively associated with joint patent quality. Coefficients of types VI (LM-H) and VIII (H-H) collaborations are positive and moderate significant ($p<0.05$), implying that these collaborations are positively related to joint patent quality.

As far as the control variables are concerned, coefficients of income difference and patent family size are negative and statistically significant ($p<0.01$). The remaining control variables are statistically significant ($p<0.01$).

Appendix 11 Model effects of PQMLE (Chapter 5)

	I	II	III	IV
Domestic university collaboration		0.15***		0.15***
		(0.01)		(0.01)
International university collaboration		0.16***		0.16***
		(0.03)		(0.03)
(I) L-L, L-LM, L-UM			-1.25**	-1.21**
			(0.61)	(0.61)
(II) LM-LM			-2.39***	-2.40***
			(0.56)	(0.56)
(III) LM-UM			-1.15***	-1.13***
			(0.33)	(0.33)
(IV) UM-UM			-1.42***	-1.41***
			(0.41)	(0.41)
(V) L-H			-0.32***	-0.30***
			(0.11)	(0.11)
(VI) LM-H			-0.27***	-0.26***
			(0.08)	(0.08)
(VII) UM-H			-0.49***	-0.48***
			(0.08)	(0.08)
(VIII) H-H			-0.30***	-0.27***
			(0.06)	(0.06)
LnIncome	-0.02***	-0.02***	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)
LnPatent	0.02***	0.02***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
LnBackward	0.76***	0.77***	0.76***	0.77***
	(0.00)	(0.00)	(0.00)	(0.00)
LnNPL	0.04***	0.02***	0.04***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Inventors	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent family size	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent claims	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent scope	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Time dummies	Yes	Yes	Yes	Yes
Observations	898,326	898,326	898,326	898,326
Degree of freedom	36	36	36	36
Log likelihood	-4.018e+06	-4.018e+06	-4.018e+06	-4.018e+06

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 11 shows the model effects of PQMLE for Chapter 5.

A consistent result with OLS is that, both coefficients of domestic and international university collaborations are positive and statistically significant ($p<0.01$). Yet, there is difference in the results of types of cross-border collaborations. Coefficients of all types of collaborations are negative and statistically significant ($p<0.01$).

As far as the control variables are concerned, coefficients of income difference (Columns I – II) and patent family size (Columns I – IV) are negative and statistically significant ($p<0.01$). The remaining control variables are statistically significant ($p<0.01$).

Appendix 12 Marginal effects of PQMLE (Chapter 5)

	I	II	III	IV
Domestic university collaboration		0.308***		0.313***
		(0.021)		(0.021)
International university collaboration		0.178***		0.196***
		(0.044)		(0.044)
(I) L-L, L-LM, L-UM			-0.244	-0.186
			(0.544)	(0.571)
(II) LM-LM			-0.928***	-0.917***
			(0.121)	(0.123)
(III) LM-UM			-0.527**	-0.501**
			(0.214)	(0.220)
(IV) UM-UM			-0.666***	-0.656***
			(0.199)	(0.200)
(V) L-H			2.253***	2.376***
			(0.347)	(0.358)
(VI) LM-H			1.491***	1.572***
			(0.203)	(0.208)
(VII) UM-H			0.045	0.085
			(0.099)	(0.101)
(VIII) H-H			0.889***	0.963***
			(0.113)	(0.117)
LnIncome	-0.087***	-0.085***	-0.122***	-0.123***
	(0.005)	(0.005)	(0.006)	(0.006)
LnPatent	0.092***	0.094***	0.055***	0.055***
	(0.004)	(0.004)	(0.006)	(0.006)
LnBackward	0.841***	0.861***	0.843***	0.864***
	(0.007)	(0.007)	(0.007)	(0.007)
LnNPL	0.001	-0.022***	0.003	-0.020**
	(0.008)	(0.008)	(0.008)	(0.008)
Inventors	0.050***	0.048***	0.051***	0.049***
	(0.002)	(0.002)	(0.002)	(0.002)
Patent family size	-0.006***	-0.006***	-0.007***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Patent claims	0.019***	0.019***	0.019***	0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
Patent scope	0.140***	0.137***	0.140***	0.137***
	(0.009)	(0.009)	(0.009)	(0.009)
Observations	898,326	898,326	898,326	898,326

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 12 reports the marginal effects of PQMLE for Chapter 5.

Coefficients of both domestic university collaboration and international university collaboration are positive and statistically significant ($p<0.01$) across both Columns. Specifically, domestic university collaboration is found to increase about 0.3 forward citations, while international university collaboration is shown to increase about 0.2 forward citations.

Coefficients of type I (L-L, L-LM, and L-UM) collaboration is insignificant although negative. Type VII (UM-H) collaboration is insignificant although positive. Coefficients of type V (L-H), VI (LM-H), and VIII (H-H) collaborations are positive and statistically significant ($p<0.01$). Lastly, coefficients of LM-LM, LM-UM, and UM-UM are negative and statistically significant ($p<0.01$).

As far as the control variables are concerned, the coefficients of income difference (LnIncome) are positive and statistically significant (Columns III – IV). The difference in patent applications across collaborative partners (LnPatent) shows strong positive and significant effect ($p<0.01$) on forward citations. The coefficients of remaining control variables, are similar to those reported by the OLS.

Appendix 13 Model effects of PQGPMLE (Chapter 5)

	I	II	III	IV
Domestic university collaboration		0.04***		0.04***
		(0.01)		(0.01)
International university collaboration		0.00		0.01
		(0.03)		(0.03)
(I) L-L, L-LM, L-UM			-0.80	-0.79
			(0.58)	(0.57)
(II) LM-LM			-1.86***	-1.86***
			(0.52)	(0.52)
(III) LM-UM			-0.77**	-0.76**
			(0.31)	(0.31)
(IV) UM-UM			-1.00**	-1.00**
			(0.43)	(0.43)
(V) L-H			0.39***	0.39***
			(0.11)	(0.11)
(VI) LM-H			0.16**	0.17**
			(0.08)	(0.08)
(VII) UM-H			-0.03	-0.02
			(0.07)	(0.07)
(VIII) H-H			0.14**	0.14**
			(0.06)	(0.06)
LnIncome	-0.00	-0.00	-0.01*	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
LnPatent	0.01**	0.01**	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
LnBackward	0.81***	0.81***	0.81***	0.81***
	(0.00)	(0.00)	(0.00)	(0.00)
LnNPL	0.13***	0.12***	0.13***	0.12***
	(0.00)	(0.00)	(0.00)	(0.00)
Inventors	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent family size	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent claims	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent scope	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Time dummies	Yes	Yes	Yes	Yes
Observations	898,326	898,326	898,326	898,326
Degree of freedom	36	36	36	36
Log likelihood	-1.586e+06	-1.586e+06	-1.586e+06	-1.586e+06

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 13 shows the model effects of PQGPMLE for Chapter 5. Compared with those of OLS and PQMLE, PQGPMLE reports different findings.

While coefficient of domestic university collaboration is positive and statistically significant ($p<0.01$) across both Columns, the coefficient of international university collaboration is insignificant although positive.

The effects of different collaborations vary. Coefficients of type I (L-L, L-LM, and L-UM) and type VII (UM-H) collaborations are insignificant although negative. Type VI (LM-H) and type VIII (H-H) collaborations show moderate positive and significant effects ($p<0.05$) on forward citations. Type V (L-H) shows a positive and significant effect ($p<0.01$) on forward citations. Lastly, coefficients of LM-LM, LM-UM, and UM-UM are negative and statistically significant.

As far as the control variables are concerned, the coefficients of income difference (LnIncome) are positive but weakly significant (Columns III – IV). The difference in patent applications across collaborative partners (LnPatent) shows moderate positive effect without adding the cross-border collaboration variables. The coefficients of remaining control variables are statistically significant.

Appendix 14 Model effects of NB1 (Chapter 5)

	I	II	III	IV
Domestic university collaboration		0.06***		0.06***
		(0.01)		(0.01)
International university collaboration		0.04***		0.05***
		(0.02)		(0.02)
(I) L-L, L-LM, L-UM			-0.59	-0.59
			(0.69)	(0.69)
(II) LM-LM			-1.55***	-1.55***
			(0.56)	(0.56)
(III) LM-UM			-0.51**	-0.50**
			(0.22)	(0.22)
(IV) UM-UM			-0.91**	-0.91**
			(0.38)	(0.38)
(V) L-H			0.10	0.10
			(0.07)	(0.07)
(VI) LM-H			0.10**	0.10**
			(0.05)	(0.05)
(VII) UM-H			-0.01	-0.01
			(0.05)	(0.05)
(VIII) H-H			0.08**	0.08**
			(0.04)	(0.04)
LnIncome	-0.01***	-0.01***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
LnPatent	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
LnBackward	0.69***	0.69***	0.69***	0.69***
	(0.00)	(0.00)	(0.00)	(0.00)
LnNPL	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Inventors	0.02***	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent family size	-0.03***	-0.03***	-0.03***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent claims	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent scope	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Time dummies	Yes	Yes	Yes	Yes
Observations	898,326	898,326	898,326	898,326
Degree of freedom	46	46	46	46
Log likelihood	-1.059e+06	-1.059e+06	-1.059e+06	-1.059e+06

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 14 reports the model effects of NB1 for Chapter 5

It emerges that the results are similar to those reported by OLS. Both coefficients of domestic university collaboration are positive and statistically significant, suggesting that university collaboration is beneficial for enhancing joint patent quality.

When it comes to cross-border collaborations, Coefficients of type II (LM-LM), III (LM-UM), and IV (UM-UM) collaborations are negative and statistically significant ($p<0.01$), suggesting that these types of collaborations are negatively associated with joint patent quality. Coefficients of types VI (LM-H) and VIII (H-H) collaborations are positive and moderate significant ($p<0.05$), implying that these collaborations are positively related to joint patent quality.

As for the control variables, income differences across partnering countries are negatively associated with joint patent value ($p<0.01$). Patent differences across partnering countries are positively associated with joint patent value. The remaining control variables are statistically significant ($p<0.01$).

Appendix 15 Model effects of NB2 (Chapter 5)

	I	II	III	IV
Domestic academic collaboration		0.02		0.02
		(0.01)		(0.01)
International academic collaboration		-0.04		-0.03
		(0.03)		(0.03)
(I) L-L, L-LM, L-UM			-0.74	-0.74
			(0.56)	(0.56)
(II) LM-LM			-1.82***	-1.82***
			(0.48)	(0.48)
(III) LM-UM			-0.73**	-0.73**
			(0.30)	(0.30)
(IV) UM-UM			-0.93**	-0.92**
			(0.43)	(0.43)
(V) L-H			0.51***	0.51***
			(0.12)	(0.12)
(VI) LM-H			0.23***	0.23***
			(0.08)	(0.08)
(VII) UM-H			0.07	0.07
			(0.08)	(0.08)
(VIII) H-H			0.22***	0.22***
			(0.06)	(0.06)
LnIncome	-0.00	-0.00	-0.02***	-0.02***
	(0.00)	(0.00)	(0.01)	(0.01)
LnPatent	0.01***	0.01***	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)
LnBackward	0.83***	0.84***	0.83***	0.83***
	(0.00)	(0.00)	(0.00)	(0.00)
LnNPL	0.18***	0.18***	0.18***	0.18***
	(0.00)	(0.00)	(0.00)	(0.00)
Inventors	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent family size	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent claims	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)
Patent scope	0.04***	0.04***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)
Time dummies	Yes	Yes	Yes	Yes
Observations	898,326	898,326	898,326	898,326
Degree of freedom	46	46	46	46
Log likelihood	-1.481e+06	-1.481e+06	-1.481e+06	-1.481e+06

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix 15 reports the model effects for NB2 for Chapter 5.

It shows that coefficient of domestic university collaboration is insignificant although positive; coefficient of international university collaboration is insignificant although negative.

The results of cross-border collaboration variables are similar to those reported by NB1. Coefficients of type II (LM-LM), III (LM-UM), and IV (UM-UM) collaborations are negative and statistically significant ($p<0.01$). Coefficients of types V (L-H), VI (LM-H), and VIII (H-H) collaborations are positive and statistically significant ($p<0.01$). Coefficient of type VII (UM-H) is insignificant although positive.

The main difference between the results reported by NB2 and NB1 is the level of significance for some country collaborations. For instance, the statistical significance of types V (L-H), VI (LM-H), and VIII (H-H) are stronger compared with those reported by NB1.

As for the control variables, income differences across partnering countries are negatively associated with joint patent value ($p<0.01$). Patent differences across partnering countries are positively associated with joint patent value. The remaining control variables are statistically significant ($p<0.01$).

Appendix 16 Model effects of OLS (Chapter 6)

	I	II	III
		Model effects	
Organisational proximity	-0.071		-0.064
	(0.189)		(0.212)
Cognitive proximity		1.986*	2.058*
		(1.018)	(1.054)
Cognitive proximity squared		-2.396**	-2.442**
		(1.009)	(1.022)
Patent scope	0.136	0.135	0.136
	(0.105)	(0.106)	(0.105)
Inventors	0.075***	0.087***	0.088***
	(0.029)	(0.030)	(0.031)
Backward citations	0.804***	0.805***	0.805***
	(0.107)	(0.107)	(0.107)
NPL citations	-0.004	-0.008	-0.012
	(0.134)	(0.126)	(0.133)
Patent family size	-0.176	-0.209*	-0.200*
	(0.121)	(0.120)	(0.121)
Patent claims	0.077***	0.079***	0.079***
	(0.021)	(0.021)	(0.021)
mechanical engineering patent	0.523*	0.453*	0.476*
	(0.273)	(0.253)	(0.273)
electrical engineering patent	-0.261	-0.346	-0.344
	(0.258)	(0.251)	(0.253)
Instrument patent	-0.462	-0.515	-0.507
	(0.372)	(0.363)	(0.369)
Observations	1,115	1,115	1,115
R-squared	0.200	0.204	0.204
Degree of freedom	30	30	30
Log likelihood	-2587	-2587	-2587

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 16 reports the model effects of OLS for Chapter 6. It shows that the coefficient of organisational proximity is insignificant although negative. The coefficient of cognitive proximity is positive and weakly significant, while that of squared cognitive proximity is negative and moderately significant. This confirms that there is an inverted U-shaped effect of cognitive proximity on joint patent quality (using forward citations).

As far as the control variables are concerned, it is found that inventors, backward citations, as well as patent claims show positive and significant effect on forward citations.

Appendix 17 Model and marginal effects of PQMLE (Chapter 6)

	I	II	III	IV	V	VI
		Model effects			Marginal effects	
Organisational proximity	-0.172		-0.176	-0.060		-0.038
	(0.177)		(0.175)	(0.163)		(0.165)
Cognitive proximity		2.093**	2.320**		1.986**	2.046**
		(1.001)	(0.999)		(1.003)	(1.039)
Cognitive proximity squared		-2.636***	-2.818***		-2.640**	-2.691**
		(1.020)	(1.016)		(1.047)	(1.072)
Patent scope	0.047	0.056	0.067	0.143**	0.150**	0.152**
	(0.058)	(0.058)	(0.058)	(0.060)	(0.059)	(0.059)
Inventors	0.084***	0.097***	0.099***	0.048*	0.064**	0.065**
	(0.024)	(0.025)	(0.025)	(0.026)	(0.027)	(0.027)
Backward citations	0.900***	0.896***	0.891***	0.887***	0.875***	0.875***
	(0.084)	(0.082)	(0.082)	(0.111)	(0.105)	(0.105)
NPL citations	-0.080	-0.084	-0.097	-0.121	-0.133	-0.136
	(0.103)	(0.100)	(0.104)	(0.099)	(0.096)	(0.100)
Patent family size	-0.240*	-0.311***	-0.278**	-0.210*	-0.262**	-0.257**
	(0.124)	(0.120)	(0.126)	(0.123)	(0.122)	(0.123)
Patent claims	0.036***	0.039***	0.039***	0.034***	0.038***	0.038***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
mechanical engineering patent	0.147	0.074	0.106	0.560**	0.522**	0.545**
	(0.240)	(0.248)	(0.244)	(0.229)	(0.222)	(0.234)
electrical engineering patent	-0.442*	-0.507**	-0.525**	-0.021	-0.098	-0.096
	(0.261)	(0.251)	(0.252)	(0.158)	(0.168)	(0.168)
Instrument patent	-0.728*	-0.697	-0.701	-0.245	-0.244	-0.238
	(0.442)	(0.434)	(0.429)	(0.279)	(0.296)	(0.296)
Observations	1,115	1,115	1,115	1,115	1,115	1,115
Degree of freedom	30	30	30			
Log likelihood	-1563	-1563	-1563			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 17 reports the model and marginal effects of PQMLE for Chapter 6. Columns I TO III show that the coefficient of organisational proximity is negative although insignificant. The coefficient of cognitive proximity is positive and moderately significant ($p<0.05$), while that of squared cognitive proximity is negative and statistically significant ($p<0.01$). Since forward citation is linked to patent quality, this suggests that there is an inverted U-shaped effect of cognitive proximity on joint patent quality. In the marginal effects shown in Columns IV to VI, cognitive proximity between partners is found to increase forward citations by about 2 units, then gradually decrease forward citations by between 2.6 and 2.7 units.

As far as the control variables are concerned, it is found that inventors, backward citations, as well as patent claims show positive and significant effect ($p<0.01$) on forward citations.

Appendix 18 Aggregations of manufacturing based on NACE Rev 1.1

Manufacturing industries	NACE Rev 1.1 codes	
High-technology	24.4	Manufacture of pharmaceuticals, medicinal chemicals and botanical products;
	30	Manufacture of office machinery and computers;
	32	Manufacture of radio, television and communication equipment and apparatus;
	33	Manufacture of medical, precision and optical instruments, watches and clocks;
	35.3	Manufacture of aircraft and spacecraft
Medium-high-technology	24	Manufacture of chemicals and chemical product, excluding 24.4 Manufacture of pharmaceuticals, medicinal chemicals and botanical products;
	29	Manufacture of machinery and equipment n.e.c. ;
	31	Manufacture of electrical machinery and apparatus n.e.c.;
	34	Manufacture of motor vehicles, trailers and semi-trailers;
	35	Manufacture of other transport equipment, excluding 35.1 Building and repairing of ships and boats and excluding 35.3 Manufacture of aircraft and spacecraft.

Medium-low-technology	23	Manufacture of coke, refined petroleum products and nuclear fuel;
	25 to 28	Manufacture of rubber and plastic products; basic metals and fabricated metal products; other non-metallic mineral products;
	35.1	Building and repairing of ships and boats
Low-technology	15 to 22	Manufacture of food products, beverages and tobacco; textiles and textile products; leather and leather products; wood and wood products; pulp, paper and paper products; publishing and printing;
	36 to 37	Manufacturing n.e.c.