Competition VS. Collaboration in the Generation and Adoption of a Sequence of New Technology

by

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To My Wife, Qiong Wu

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Declaration

To the best of my knowledge, all the work in this thesis is original.

No part of this thesis has been submitted for a degree at another university.

All work is entirely my own. Part of Chapter 2 and Chapter 3 in this thesis has been presented at DRUID summer conference 2009.

The software we used are Matlab for theoretical model, and Stata for empirical analysis, respectively.

Abstract

Although there is quite a rich literature relating to competitive innovation there is relatively little relating to technological collaboration. However, ignoring collaborative possibilities may result in overestimation of the importance of self-innovation. This thesis is therefore mainly concerned with the determinants of collaboration in innovation, taking both a theoretical and an empirical approach. The empirics relate to the manufacturing industry in a Chinese region. The thesis is particularly innovative in emphasising how collaboration costs will be shared when collaboration occurs.

We provide a game theoretic exploration of the decisions of firms on whether to compete or collaborate in the generation and adoption of a sequence of new technologies. Different from the models proposed by Vickers, who concentrates upon process innovation and a two-strategy (innovation or do nothing) set, our game theory model emphasises product innovation and either a three-strategy set (innovation, collaboration, and do nothing), or a four-strategy set (innovation, collaboration, imitation and do nothing). In particular, MATLAB programming is employed for generating the equilibrium solution for each strategy set. We found that the relationship between imitation and collaboration and collaboration cost is not univariate. It depends upon the market type and various market characteristics, such as technology gap, technology level, the product substitution index, transaction costs and the discount rate of price sensitiveness. The results also show that the elasticity of collaboration opportunity with respect to transaction costs in a persistent dominance market is much greater than in an action reaction market.

By using data on manufacturing in a Chinese region from 2005 to 2007, derived from the China Innovation Survey and the Annual Corporate Financial Survey, we empirically explored innovation and collaboration patterns. Three factors, innovative ability, absorptive capacity, and catching up capacity were proposed to positively affect both innovation and collaboration. This led to six hypotheses, which were tested using a number of econometric models encompassing selection bias, timing, and dynamics issues. The major finding from the empirical models suggests that innovative ability, absorptive capacity and catching up capacity all impact significantly and positively on collaboration, whilst innovation is positively related only to absorptive capacity. Also, we found that collaboration cost may increase with R&D, employees' education, the technology gap and collaboration cost in previous periods, but decrease with transaction cost, patents held, the technology level and perceived price.

The thesis makes three contributions. Theoretically, our game theory model not only extends the understanding of the impacts of collaboration possibilities and collaboration cost in dynamic game theory, but also clarifies the impacts of transaction costs and imitation (and thus intellectual property rights (IPR)) on the outcome. Empirically, by introducing new data our work is the first to investigate collaboration patterns and collaboration cost sharing strategies in a mid-income level developing country. Last but not least, using MATLAB animation programming to simplify the calculation process of the game theory equilibrium may be considered as a methodological contribution.

1 Introduction

1.1 Motivation and Concepts

As Solow (1956) identified, the main driver of economic growth is improvements in technology. This has led to a long-running and extensive interest in the study of innovation and related topics. One issue is whether firms may prefer to innovate alone or to collaborate in the innovative process with others (be it with other horizontally or vertically related firms, or unrelated firms, or even public bodies). To date, there has been little agreement on when collaboration might be optimal especially in the case of product (as opposed to process innovation). In today's highly competitive environment where innovation is critical (Andersson & Kaplan, 2004), to some extent it may be the best strategy for firms to collaborate with rivals to, for example, share the cost burden of product development. Such arguments imply that collaboration may be an important strategy as firms compete in technology. Ignoring the possibility of collaboration could result in an overestimation of the importance of other determinants of innovation, such as R&D (Love & Roper, 1999). There are thus good reasons for looking again at collaboration in technology development.

This research has two main components. The first is a theoretical component in which game theoretic models are employed to analyse when and where firms might collaborate and how the costs of collaboration may be shared. This is innovative in a number of ways as we detail below. The second component is empirical and explores patterns of innovation and collaboration in the manufacturing industry in a Chinese district. This is also innovative in that to the best of our knowledge such sample data has not been previously explored, and thus what we deduce about patterns of innovation and collaboration and their determinants in this example are new to the literature.

The determinants of whether and when firms collaborate has been a controversial and disputed subject even within the limited field of collaboration research. The main suggestion in the literature is that collaboration may bring firms higher profits/welfare (Seade, 1980; Motta, 1992; Rosenkranz, 1995). On the other hand, some scholars believe that the driving force behind collaboration is the impact upon the extent of product sales (Buckley & Casson, 1996) and generating global sustainable competitive advantage (Zhang et al., 2007; Feng & Chen, 2004).

However, if collaboration is always a better strategy, then one cannot explain why firms do not always choose collaboration. As Xu and Zhang (2008) found in a study of 541 Chinese publicly traded companies from 2000 to 2005, firms sometimes prefer innovating independently rather than collaborating. This leads us to ask: under what conditions will firms collaborate and under what conditions will they not? We are particularly interested in mapping those forces that condition collaboration in order to illustrate incentives to collaborate.

The work of Gan et al (2002) is also relevant. In their empirical analysis, they examined the different profit rates from two strategies, being an upstream supplier or being a horizontal competitor. Similarly, in order to understand why and when firms collaborate, we explore whether the payoffs to collaboration and innovation strategies differ.

The purpose of this thesis therefore, is to examine the determinants of innovation and collaboration by firms facing a sequence of potential new technologies that they may generate and/or adopt. In addition we also wish to explore how the costs of innovation under collaboration are shared between the collaborators when collaboration occurs.

Throughout this research the term collaboration is taken as involving 'strategic alliances', although sometimes the label 'collective integration' may be used. Parkhe (1991, 1993) suggests that a strategic alliance refers to *'relatively enduring interfirm cooperative arrangements',* which allow firms to serve their individual needs by utilising mutual resources. But this definition does not distinguish collaboration from cooperation. As collaboration and cooperation are similar or synonymous concepts, this may cause confusion. Therefore, by following the alternative definition of collaboration suggested by Polenske (2004), collaborative relationships in our thesis are defined to *'include direct participation by two or more actors in designing, producing and /or marketing a product'*, whilst cooperation relationships are defined as when *'two or more actors agree through formal or informal arrangements to share information, support managerial and technical training, supply capital, and/ or provide market information'*.

This definition allows us to further distinguish collaboration from joint ventures, which normally refer to investment alliances rather than the alliances in generating and introducing new technology. In general, collaboration may be considered as one particular form of joint venture. In some literatures, collaboration is regarded as one kind of knowledge sharing joint venture, which may be configured in many different ways and associated with different kinds of behaviours. As Buckley and Casson (1996) suggest in their internalisation theory model, the typology of joint ventures may be classified into three kinds:

technology sharing, marketing sharing, and both. Only pure technology sharing joint ventures may be recognised as R&D collaboration. However, the idea of a 'knowledge shared kind of joint venture' may not be accepted by others. Luo (1997) for instance, divides joint ventures into two categories using either operation-related criteria or cooperation-related criteria, suggesting that along with operation-related criteria which cover the strategic traits of partners, including absorptive capacity, market position and the degree of product differentiation, collaboration, together with organisational form and size, may be seen as components of cooperation-related criteria.

In our work we concentrate upon (i) technological collaboration between firms in the same product market in our game theory modelling, and (ii) technological collaboration more generally, encompassing that between firms, institutions, universities, and even government, in our empirical analysis.

1.2 Overview

The main areas where this study will particularly contribute are:

- To extend the existing theoretical academic literature on innovation games by taking collaboration and imitation into account, and showing the influences on the outcomes of dynamic games brought about by allowing collaboration and imitation;
- To concentrate upon the determinants of both collaboration and innovation patterns more generally, emphasising product rather than process innovation;

To explore the determinants of collaboration and the sharing of collaboration costs by designing and using a set of MATLAB animation programmes;

To use panel data upon Chinese manufacturing firms from 2005 to 2007 to explore whether innovative ability, absorptive capacity, and catching up capacity significantly influence firms' innovative (or collaborative) decisions;

To illustrate the policy implications at both firm and national levels on the basis of the empirical results.

In outline, Chapter 2 reviews the existing literature on collaboration and related topics. This chapter can be roughly divided into two parts. The first part explores the literature regarding firm strategies under technological competition, such as self-innovation and imitation. The drawbacks of undertaking such analysis without considering collaboration possibilities are particularly mentioned. The second part describes the limited existing research on collaboration compared to the analysis of competitive strategies and introduces relevant theories, such as Intellectual Property Rights theory, transaction cost theory, and strategic management theory. In particular, we consider the classification of different types of collaboration and the distinction between collaboration and joint ventures. We also explore the possible impacts of collaboration on innovation and product market competition.

Chapter 3 addresses a game theory model inspired by Vickers (1986). It begins by expanding Vickers' game theoretic two goods, two players model where firms may either self-innovate or not innovate by adding collaboration and imitation options and exploring product innovation rather than process innovation. The conditions that have to be met for firms to collaborate in three-strategy set, (collaboration, innovation, do nothing) and four-strategy set (collaboration, innovation, imitation, do nothing) worlds are discussed separately. We then propose as an example, a model inspired by Shaked & Sutton (2007), and Matsubayashi (2007) to investigate further the conditions under which collaboration will occur under each of the strategy sets. Since a number of market parameters have non-constant impacts on collaboration costs and the incentives to collaborate, the analysis is pursued by the use of a number of dynamic and 3-D graphics generated by programming a MATLAB animation. Further predictions are then generated by observing equilibrium changes illustrated in the MATLAB graphics.

Chapter 4 introduces our data related to Nan Chang in China and comes from the 'China Innovation Survey' and the 'Annual Corporate Financial Survey' from 2005 to 2007. We explain the reason why we chose Nan Chang as the object of our empirical studies, and the way we cooperated with the data owner, the National Bureau of Statistics of China (NBSC). In the initial analysis of the nature of the sample and panel characteristics, we compare major economic indicators between Nan Chang, Jiang Xi and China as a whole to illustrate the relevance of the sample.

We argue that because of data limitations, it will be impossible to directly empirically test the game theory predictions of Chapter 3. Therefore, we propose in Chapter 4 (and further develop in Chapter 5) a series of relationships whereby innovation, collaboration and cost sharing are related to firms' innovative ability, absorptive capacity, and catching up capacity. In order to allow us to test relevant hypotheses, we then go on to define an array of relevant indicators. After first exploring the distribution of collaboration and innovation in the data, we look at sample characteristics including differences in patterns by ownership and regions.

Chapter 5 uses the Chinese manufacturing industry data to econometrically explore a number of testable hypotheses on the determinants of innovation, collaboration and collaboration cost shares. As the estimates could be biased if we ignore sample selection effects, we first employ the general Heckman model and Heckman Probit sample selection models, separately. As no selection bias was found, we then propose using Probit models for regressing relating to the binary variables, innovation and collaboration, whilst employing OLS, fixed effect and random effect models for collaboration cost estimation. Finally, we extend the empirical analysis by taking time dummies and one period lagged dependent variables into account to investigate timing and dynamics issues. The results indicate that (aside from any dynamic influence), all three factors, innovative ability, absorptive capacity, and catching up capacity are positively related to collaboration, whilst only absorptive capacity is positively related to innovation (including both self-innovation and collaborative innovation). We also found that collaboration cost may be positively influenced by R&D, employees' education, the technology gap, and collaboration costs in previous periods, but negatively affected by transaction costs, patents held, the technology level and perceived price.

Chapter 6 extracts the significant findings from each chapter illustrating the linkages. Contributions upon three categories are discussed. In addition we also consider some of the limitations of our research and provide some recommendations for future research.

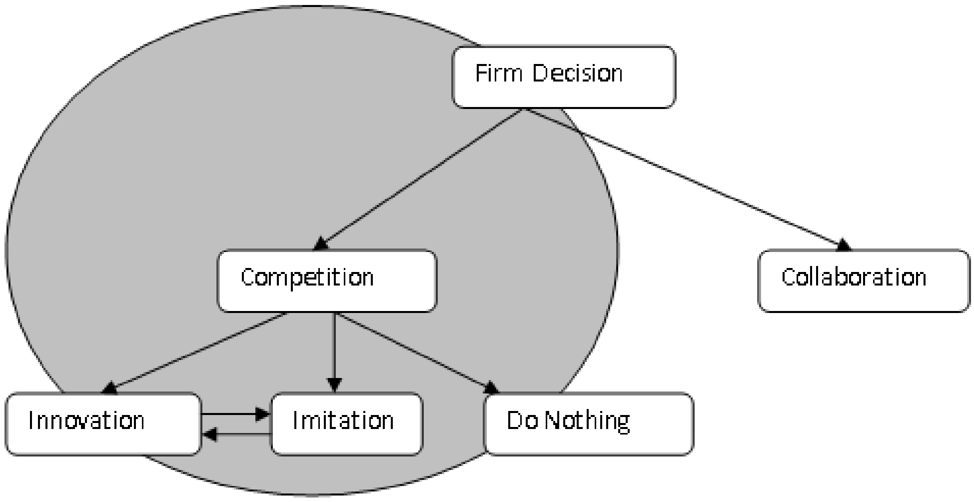
2 Literature Review

2.1 Introduction

The idea that technological advance plays a major role in the determination of advances in economic prosperity is now widely accepted in both academic and policy arenas (Love & Roper, 2004). The main objective of this thesis is to examine the nature and determinants of firms' optimal innovation strategies in product markets on which they compete via product enhancement or innovation, and to pursue the implications for firm's performance and economic welfare. There are two main emphases in the research. The first is an emphasis upon collaboration between firms. The second emphasis is on the Chinese manufacturing sector as the main empirical test bed. The latter choice is largely conditioned by a dearth of studies of such issues in developing countries. The former choice is a natural extension to existing literatures

Most prior theoretical work (and especially the creative destruction approach, Schumpeter, 1934), allowed firms to face three main innovatory options - doing nothing, innovating (being first) or imitating (not being first) (as illustrated on the left hand side of Figure 2.1 below). A first objective in this literature survey is to review matters relating to the choice between these three options and to illustrate the difference in their impact.

Figure 2.1 Innovation Strategies



There is however an alternative strategy to competition which we label collaboration. This we define more precisely below but may encompass a number of activities from joint research ventures and joint product development through to licensing and other related activities. In terms of a decision tree (see the right hand side of Figure 2.1) one may consider that there is a high level strategy choice that a firm needs to make (between competition and collaboration) prior to deciding whether to innovate, imitate or do nothing. It is this alternative higher level strategy choice that this thesis is mainly directed to explore.

In the sections that follow we first explore the traditional literature that assumes competition in innovation with some emphasis upon Schumpeterian models and empirical findings in a Chinese context, and then explore (Section 2.2.2) the relationship between innovation and imitation before considering the impact of the degree of competition upon innovation (Section 2.2.3)

Section 2.3 introduces the alternative firm strategy choice, collaboration. In particular, section 2.3.1 examines cooperation effects in competitive environments. Section 2.3.2 discusses different approaches to definitions of collaboration. Section 2.3.3 discusses the difference between collaboration and joint ventures. Section 2.3.4 addresses various incentives to collaboration and non-collaboration by using game theoretic and other approaches. Section 2.3.5, section 2.3.6 and section 2.3.7 respectively explore the impact on decisions to collaborate of intellectual property rights, transaction costs, and strategic management issues. Sections 2.3.8 and 2.3.9 discuss the connection between collaboration and product market competition and collaboration and innovation respectively.

Finally Section 2.4 draws conclusions from the literature review on the determinants of research collaboration, initially in general terms and then in terms of the Chinese experience. This provides the introduction to the following chapters that address the deficiencies in our knowledge thus noted.

2.2 Strategies Assuming Competition

2.2.1 Introduction: The Determinants of Innovation Activity

There is now a huge literature upon innovation, both theoretical and empirical. It is beyond the scope of this thesis to review all such literature. The reader is instead referred to the recent Handbooks by Stoneman (1995) or Hall & Rosenberg (2010). Instead we undertake a much less ambitious task in this sub section. First we introduce the idea of creative destruction as a useful basis for some later ideas and then we provide an overview of empirical findings relative to China, these being much less easily accessible.

The concept of the ‘process of creative destruction’ introduced by Schumpeter (1934) has played an important role in the literature on the economics of innovation. In the context of a product market in which firms compete, it is argued that firms earn returns to innovative activity by creating a temporary monopoly from which monopoly profits may be earned. The firm however, only enjoys temporary monopoly power as a result of innovation because its monopoly can be overturned by a later inventive challenger. The incumbent can only enjoy the monopoly benefit until a newer innovation comes along. After that, the profits will be captured by other innovators. Although later innovators build upon the basis of the previous innovation, they do not compensate the previous innovator. In other words, the market has neither memory nor spillover effects.

The value of being the incumbent firm will be lower the greater the number of future innovations that may be made. Also, under additional conditions, the value of being a challenger will increase with the number of potential future innovations. As a consequence of these two results, both the incumbent and challengers alike will invest less in the current innovation when a greater number of future innovations are anticipated.

In a Schumpeterian framework, the relationship between the amounts of research undertaken to produce innovations in two successive periods can be modelled as deterministic. Aghion & Howitt (1992) build a model in which each innovation creates a cross sectional monopoly in the production of intermediate goods. They then suggest that a foreseen increase in research in the next period discourages research during the current period: by raising future wages and hence reducing the flow of profits to be captured from the next innovation; and by raising the rate of creative destruction next period and hence shortening the expected lifetime of the monopoly to be enjoyed by the next innovator. One equilibrium in their model, labelled “two-cycle”, defines a perfect foresight equilibrium in period two. *'In a real two-cycle, the prospect of high research in odd intervals discourages research in even intervals, and the prospect of low research in even intervals stimulates research in odd intervals'* (as illustrated in Table 2.1). This model appears to be a clear modern interpretation of Schumpeter's ideas.

Table 2.1 The Two Cycle Model

Odd interval	**Even interval**	**Odd interval**	**Even interval**	…..
High Research	→ *Discourage research*	← High Research	→ *Discourage research* ←	……
Stimulate Research ←	Low Research →	*Stimulate Research* ←	Low Research →	…..

Although very little empirical work directly relates to this Schumpeterian framework it is useful to here introduce some empirical findings upon the determinants of innovative activity. We concentrate upon findings relating to China, for these are less easily accessible than many others and are particularly relevant to this thesis.

Tu and Yi (2008) studied China's self-innovation capability by addressing the causality between self-innovation and its determinants. They first employed factor analysis to clarify groups with different innovation capabilities across 31 regions in China. Then they illustrated a multi-regression model by assuming four innovation determinants, the R&D level, human resource (HR) input, net import-export revenue, and foreign direct investment (FDI). Chinese industry panel data from 1996-2005 are used. In their findings, we notice that the first three of the four determinants could significantly stimulate self-innovation. However, the last determinant in their model, FDI, has a negative impact.

As current Chinese policy is to make a transition from a centrally-planned economy to a free enterprise economy (Mehta et al, 2006; Yergin & Stanislaw, 2002), FDI plays an important role as a means to inject foreign capital and ideas into the country. On the other hand learning orientation and ‘learning-how-to-learn’ are especially strong in China. It is thus particularly important for China to understand whether FDI can directly stimulate the amount of innovation, or whether FDI can influence innovation through knowledge sharing. Thus in addition to looking at other possible innovation determinants, such as R&D, it is of particular interest in the Chinese context to explore literatures relating to FDI and innovation.

Similarly to the work of Tu and Yi (2008), non-positive links between FDI and innovation capability can also be found in other work. Zhang (2008) examined the impact of FDI on the self-innovation capability of Chinese home manufacturing. He used panel data models (both fixed effect and random effect models) with Chinese data encompassing 28 major industries from 1999 to 2003. He found that in traditional industries, only factor endowment and technical opportunity have a significant impact, whilst FDI, payoff ability, government funding and the degree of market competition do not affect innovation capability. In particular, in high-tech industry, the only significant determinant is technical opportunity. On the other hand, FDI has a positive impact on self-innovation and spillover effects, although such impact mainly comes via the demand side of innovation capability.

In contrast, some other studies show evidence of the ambiguous relationship between FDI and spillover effects e.g. Chen (2006). Instead of focusing on the spillover effect of intra technology diffusion, Chen (2006) examined the vertical spillover effect of inter-technology diffusion. Differentiation models and a dynamic GMM method with 7 years of panel data at the industry level (including 24 Chinese manufacturing industries) are used. The author looked at the change in revenue value added and used the FDI proportion as the spillover index. He suggests that there is a strong U shaped relationship between the FDI level and the spillover effect. In particular, a significant backward inter-diffusion spillover effect was found, which suggests that state owned firms may benefit from technology generation by offering intermediate products to firms with external ownership (Guo & Zhang, 2008). This does not necessarily imply that firms with external ownership seldom innovate. Rather, Love and Roper (1999) suggest that it is because many externally-owned establishments are presumably branch plants, dependent on inputs from elsewhere. Lastly, there is no significant positive impact of R&D on productivity and the spillover effect.

In a different vein, Ping (2007) analyses the FDI spillover effect on Chinese firms, using an OLS model and cross sectional data to prove that ownership plays an important role. Only FDI from Hong Kong, Macau and Taiwan has an explicit positive spillover effect, whist other FDI from foreign owned firms has no significant impact. Interestingly, he finds that the innovation capability and activity of Chinese local firms even decreased after foreign FDI's entry. This finding is slightly different from that in previous studies.

However, other recent empirical studies about the impact of FDI on innovation capability illustrate that a positive relationship may exist. Girma et al. (2008) employed data from China's Annual Reports of Industrial Enterprise Statistics from 1999 to 2005 (including more than 200 thousand domestic firms) to test if FDI and foreign capital play a significant role in innovation activity. The Tobit regression result shows that, both foreign capital and FDI are positively associated with innovation activity. The reason for this phenomenon could be explained by two aspects: on the one hand, FDI could impact on innovation directly because inward FDI may loosen financial constraints, which allows firms to purchase or update new technology easily; on the other hand, FDI may positively influence spillover effects and consequently indirectly impact on innovation.

Girma & Gong (2008), also argue that domestic firms, which have been injected with knowledge by FDI from technologically advanced firms, are also more able to engage in innovation activities. However, it seems that such a relationship depends upon ownership as well. For Chinese state owned enterprises (SOEs), which monopolise financial resources, a negative relationship between inward FDI in the sector and innovation may be found (Girma et al, 2006; 2009).

All such findings are relevant to the wider picture of innovation in Chinese manufacturing. They do not however, nor does the Schumpeter approach, consider whether it is better, under a competitive strategy, for firms to lead in innovation or imitate rivals. It is to this question that we now turn.

2.2.2 Innovation and Imitation

There is ample evidence that firms imitate and copy the innovations of others. For example Tilton (1971) found that the time lag between the initial discovery of semiconductor innovations by American firms and the first commercial production by Japanese firms averaged just 1 year. Mansfield et al (1981) found that 60 per cent of the patented innovations they studied were imitated within 4 years. As there have been no systematic empirical studies of the speed at which various kinds of technological information leak out to rival firms, Mansfield

(1985) also filled this gap after his investigation of 100 American firms and found that the leak out speed of new processes and new products differ. Process developments tend to leak out more slowly than product developments in practically all industries. But the difference, on the average, is less than 6 months.

These results have important implications not only for incentives to innovation, but also for helping us to understand the imitation effect on economic growth. Our particular interest however is in the determinants of the incentives to lead or follow.

In a dynamic equilibrium model of product innovation (generated from an innovation growth model by Grossman & Helpman, 1991c), Segerstrom (1991) found that the model had a steady-state equilibrium in which the rate of economic growth is constant over time. In this steady-state equilibrium, *'firms engage in both costly innovative and costly imitative activities, although not in the same industry at the same time'*. It seems to be more profitable to imitate with a single leader and more profitable to innovate with two leaders. Segerstrom (1991) also gives us a connection between innovation and imitation. He claims that *'increases in government subsidy to innovation unambiguously increases the steady-state intensity of imitative effort in each industry in which firms engage in imitative R&D; and increases in the government subsidy to imitation increases the intensity of innovative effort in each industry in which firms engage in innovative R&D'*. In other words, *'cheaper innovation implies a faster rate of imitation, whilst cheaper imitation implies a faster rate of innovation'*.

Liu and Shi (2007) build a game-theory model based on the Romer's leader-follower perspective which offers an alternative way to reveal the link between innovation and imitation. They deduce that innovation is linked negatively with its cost, but positively with labour input; whilst imitation is linked positively with innovation costs, but negatively with labour input.

Sun and Cui (2007) believe that when there are technical and cost differences, a Nash equilibrium solution may involve the technology leading firm engaging in innovation, and the technology follower engaging in imitation. In contrast, when there are no technical and cost differences, it is an optimal gambling strategy for both firms to choose innovation at the same time. However, as the authors state in their conclusion, in terms of gaining higher welfare and profit, collaboration or joint venture may be alternative effective strategy for firms.

However, other scholars disagree. By building a two-player game theoretic model, Peng and Li, (2008) conclude that imitation is always the dominant strategy for both firms in a strategy set with only innovation and imitation options.

Such literature as this suggests that there may be optimal strategies that involve some firms imitating rather than leading. We do not however have any specific empirical evidence relating to China upon this. We thus turn to consider the largest body of literature relating to behaviour when firms compete in innovation – that which relates to the impact of the degree of product market competition.

2.2.3 Traditional Strategies: The Impact of Competition

Schumpeter (1934) suggested that there should be a negative relationship between competition and innovation. This prediction has been subject to much further study and there is a rich array of industrial organisation theory and empirics that addresses the issue. Much, but by no means of all of this work predicts that innovation should decline as the degree of product market competition increases (at least up to some limit).

We cannot possibly summarise all this work here, so once again the reader is referred to Hall et al (2010). Considering some of the more recent work, however Aghion, Bloom, Blundell, Griffith and Howitt (2005) developed an extension to the work of Aghion, Harris, and Vickers (1997) and Aghion, Harris, Howitt, and Vickers (2001). They continue to assume that both current technological leaders and followers in any industry can innovate, and the innovation type is step-by-step, implying the two firms are in a neck-and-neck relationship. However, although Schumpeter claimed that the incentive to innovation comes from becoming an incumbent firm in a competitive market with monopoly profit (whilst other followers in that industry gain nothing or even lose part of their pre innovation profit), Aghion et al (2005) suggest that such innovation incentives should not depend so much upon post-innovation rents, but upon the differences between post-innovation and pre-innovation rents of incumbent firms. In other words, more competition may increase the incremental profits from innovating, and of course, encourage R&D investments. This effect is called an ‘escaping competition’ effect. One may note that greater competition may still reduce innovation incentives for laggards, which may be called a ‘Schumpeterian’ effect. Both the escaping competition effect and Schumpeterian effect jointly influence the balance of the competition—innovation relationship over time to time.

Overall therefore the outcome is driven by the strength of each effect when competition changes from low to high. This observation leads to the main conclusion: the relationship between competition and innovation is nonlinear and in fact is an inverted-U shape. More specifically, when the competition intensity is high, the extent of innovation would be high in neck and neck sectors, called *'leveled'* sectors where both firms stay at same technology level, whilst the intensity of innovation activities will be low in leader-follower sectors, called *'unleveled'* sector, where a technology gap between the two firms is maintained. Overall it means that the escaping competition effect is more likely to dominate the Schumpeterian effect and firms prefer faster innovation with increasing competition when the competition intensity is low. On the other hand, when competition is high, the industry will spend most of the time in the unleveled state where the Schumpeterian effect is at work on the laggard, while the leader never innovates. In other words, the Schumpeterian effect is more likely to dominate and the incentive of innovation declines with increasing competition.

Reinganum (1985) however draws some different conclusions on the relationship between innovation and competition. Extending previous contributions assuming a single innovation and outsider followers (competitors), Reinganum (1985) allowed for multiple innovations and inside challengers. She generated a fully optimizing behavioural model based upon the Schumpeterian 'Creative Destruction' process and obtained a stable equilibrium, within which are included predictions on the relationship of investment (on innovative R&D)

and competition. As investment in R&D is vital to the size of innovation, deductions from such connections found in the Nash equilibrium of her model may be useful for figuring out the relationship between competition and innovation. She suggested that the investment rate of challengers increases with an increase in the discount rate, the value of being the incumbent next period, and the number of firms in the industry. The investment rate of each challenger decreases in response to an increase in the profit associated with the current innovation or the value of being a challenger next period and vice versa. The incumbent's rate of investment increases with an increase in the discount rate, the value of being the incumbent next period, and the number of firms in the industry. The incumbent's rate of investment decreases in response to an increase in the flow revenue associated with the current innovation or an increase in the value to being a challenger in the next stage. Since this model is based on the flow cost model of Lee and Wilde (1980), it is not surprising that she concludes that an increase in the number of firms (challengers) leads to an increase in the rate of expenditure for each firm, and the aggregate rate of investment. Therefore, the faster the pace of innovative activity (the average time between innovations is shorter which some articles call innovation frequency); the greater is the number of challengers, i.e., the more competitions.

Vickers (1986) further investigated Reinganum's idea (1985) of a relationship between innovator and follower by proposing a bidding patent race in a duopoly market. He assumed both players face a sequence of opportunities to innovate. In particular, any innovation, with inviolable IPR, will be granted to the player who offers the highest bids. The author divides the resulting markets into two groups. One is a persistent dominance market, suggesting that the same player is the winner in each round. The other is an action reaction market, indicating a leapfrogging outcome in which the winner in the current round will be the loser in next round. After analysing a simple duopoly model illustrated with homogeneous products, Vickers claims that a highly competitive product market results in persistent dominance, whilst Cournot behaviour leads to action reaction. This model, however, has some clear drawbacks. One is that the innovations he proposes are process innovations that emphasise the cost efficiency effect with product innovations put on one side. Another shortcoming is that he assumes that players may innovate or not innovate and ignores other possibilities, such as imitation, or collaboration. This limits the credibility of this work.

As stated above there is a huge theoretical literature that is still not conclusive. Similarly, there is a very large empirical literature upon the competition-innovation relationship. There is however only limited empirical research on the Chinese context. However, Girma et al. (2006) explored the impact of FDI on innovation via the degree of competition as an intermediary. They explore the innovation performance of Chinese State Owned Enterprises (SOEs) from 1999-2005 via a lagged FDI term. They found an inverted-U shape relationship. The result shows that FDI in laggard SOEs normally diminishes innovation activity, whilst SOEs with a small technology gap may be stimulated when there is increased FDI.

2.3 Alternative Strategy, Collaboration

2.3.1 Competition vs. Collaboration

From the above section, it is clear that, starting with Schumpeter's idea of creative destruction, research has proceeded using many different models and various data sets to address the main issue. Recent work however has concentrated on one sub-branch of the decision tree (Figure 2.1) allowing for example neck-and-neck duopoly, costly entry, and decreasing returns to scale. And this issue seems to have been well researched. Much less studied however has been a consideration of what will happen if firms instead of pursuing a competition strategy pursue a collaboration strategy. This is the area to which this research is mainly directed.

Studies by Gans et al (2002) confirm the importance of this interest. They examine whether the returns to innovation are earned through product market competition or through cooperation with established firms (through licensing, alliances, or acquisition). The panel data they used comes from the biotechnology industry. This industry is a high-tech one and depends heavily upon technology replacement and patent protection. They examined different profit rates from two alternative firm strategies, being an upstream supplier of technology and being a horizontal innovation oriented competitor. They conclude that the returns to such firm strategies depend upon control over intellectual property rights (IPR), transaction costs and sunk costs associated with product market entry. This inspires us to consider that we should take collaboration into account when we study firms' innovation strategies.

The traditional analysis of innovation has focused on the Schumpeterian hypothesis of a positive link between market power and innovation. That approach leads to a further investigation of the impact of market power and firm size on R&D and innovation. Indeed, much previous literature finds that there is a positive relationship between firms' sizes and innovation. However, the weakness of the empirical evidence for the Schumpeterian hypothesis raises some doubt on the validity of this linear view of innovation process. To solve this problem, Pennings and Harianto (1992) claim that self-technology accumulation and networking may play an important role when firms innovate. They examined a sample of US commercial banks during the period 1977-1987, some of which were engaged in a new technology: home banking. The authors used an event-study approach to show that firms with intensive networking may behave actively on innovation with their strategic partners.

Similar views are supported by later studies. Love & Roper (1999) also suggest that we need to take collaboration (networking) and technology diffusion (transfer) into account when discussing innovation. They extend the standard Schumpeterian explanation of firms' innovative activity to do so. Using a unique dataset re UK manufacturing plants they conclude that technology transfer and networking are crucially important substitutes for R&D in the innovation process rather than complementary inputs. Failure to consider them may lead to an overestimation of the effect of R&D on firm performance. On the other hand, the finding suggests that the market power could reduce networking intensity, which contrasts with the idea of Schumpeterian competition. Lastly they find that firm size exhibits no influence on the intensity of R&D or technology transfer, but is positively linked with networking.

In fact, according to the supply pattern hypotheses suggested by Andersson & Kaplan (2004), firms have two basic sources of capability acquisition. Supply can come from either internal sources (in-house innovation and cloning-replication) or external sources (collaboration, firm purchasing and cloning-imitation, with cloning-emulation taking a middle form). However, in today's highly competitive environment, a business's ability to keep up with technological progress and to continuously innovate, which is the so-called internal source, is critical for its survival and growth. However, because of the constraints of limited resources, it is increasingly difficult for firms to develop new technologies entirely on their own (Hamel & Prahalad, 1994). Therefore, collaboration is an alternative way to meet the growing demand for industrial innovation in the global market place, although in particular cases, internal capability acquisition is still emphasised as important, if it is possible (Andersson & Kaplan, 2004).

Specifically, in economic environments such as high-tech industry, where development and growth closely relate to intellectual property rights, firms face high relative investment costs when they innovate. Therefore, in the case of strong competition and anti-trust policy, when firms intend to develop and introduce new products, they may choose an alternative strategy to competing to win the competition race, i.e. they may choose to collaborate. Nueno and Oosterveld (1988) argue for example that the cost minimising firm could be a hybrid organisations undertaking for example cooperation on technologies via strategic alliances.

Empirical evidence in the Chinese context on collaboration is limited. One noticeable piece is by Xu and Zhang (2008) who examine the impact of state shares on innovation and performance in China by using both OLS and logistic models. The authors investigated 541 publicly traded companies in five high-tech industries during the period from 2000 to 2005. The result shows that, to achieve a better performance, firms with state shares prefer process innovation rather than product innovation, and interestingly, they prefer innovating independently rather than collaboratively.

These literatures naturally lead us to a question: is it really true and possible that the firm to obtain more innovation rents when it collaborates with others rather than innovating and imitating independently? To answer this question, we have to make clear what incentives push firms to collaborate and of what factors firms are aware when collaboration fails. Prior to discussing relevant literatures it is however first useful to define and classify collaboration.

2.3.2 The Definition and Classification of Collaboration

There are alternative labels for the activity of technological collaboration. Various terms such as collective integration, collaboration, and strategic alliances have all been used. Building upon the definition by Aderson and Narus (1990) that cooperation is *'similar or complementary coordinated actions taken by firms in interdependent relationships to achieve mutual outcomes with expected reciprocation over time'* (Mehta et al, 2006), Parkhe (1991, 1993) suggests that a strategic alliance refers to *'relatively enduring interfirm cooperative arrangements',* which allows firms to fully utilise mutual resource while serving individual goals to each sponsor. Man & Duysters (2005) alternatively describe a strategic alliance as cooperative agreements in which two or more separate organisations team up in order to share reciprocal inputs while maintaining their own identities.

References in the literature to strategic alliance are seldom found before the 1980s. The period of strong growth of strategic alliances starts at the end of the last century and coincides with faster world technological change. Many firms began after the 1980's to undertake their innovation projects through new forms of cooperation, such as joint ventures, collaboration and various other types of joint development agreements. But after a growing number of alliances in the post 1980s, scholars seemed to realise that strategic alliances cannot solve all problems. In particular, it was noted that the success rate of alliances is still at a low level (about 50% or even less). However, a further increase in competitive pressure and the rising costs of R&D accelerated the formation of strategic technology once again in the mid-1990s. '*Today, alliances have become an important vehicle for keeping up with turbulent technological change, even though average alliance success rates remained poor'* (Man & Duysters, 2005).

Corporate inter-firm alliances may also be defined as *'collaboration between independent firms over a given economic space and time for the attainment of mutually defined goals'* (Glaister & Buckley, 1992). *'The existing literature has classified alliances primarily on the basis of their governance structures'* (Yoshino & Rangan, 1995). Two main categories are popular, equity and non-equity alliances. *'Alliances have also been classified in terms of geographic and political scope, named as domestic and international alliances'* (Adobor, 2006). Although classifications of alliances can be useful, existing classifications may not match well with the reality of collective firms. Adobor (2006) includes other forms or sources of cooperative strategies and presents four different forms of alliances:

a). The first type of alliance involves spontaneous emergence, and in such alliances cooperation (labelled as tacit (Axelrod, 1984)) is informal with no explicit agreement governing the relationship. A spontaneous form of inter-firm collaboration may emerge as result of natural but informal connection. Several factors may explain such an alliance:

'First, geographic boundedeness increases the frequency of social interaction, including trust building; Second, common perception of threats or a realisation of shared interests can lead to the rise of spontaneous cooperation, although in some cases, it may take a third party to help… Wine production in France may be an example of a case where a common perception of shared threats and shared social norms may explain the emergence of cooperation.'

Abraham & Fombrun (1994) discuss the idea that widely shared organisational-related beliefs across organisations (macro cultures) could also encourage cooperation. Alliances associated with spontaneous forms are more likely to be informal and non-equity based than alliances formed formally or those formed with the assistance of third parties.

b). The second type of alliance is individual firm initiated alliance forms, initiated by two independent firms, which are perhaps the most common types of cooperative strategy discussed in the literature. Such alliances range from domestic to international. A number of factors may lead to these forms of alliance. First, firms may initiate an alliance because they see a mutual benefit from the relationship. Second, a cooperative strategy as a strategic choice may be used to share the cost of new product development or as a way of gaining access to both domestic and international markets. Thirdly, in some cases, alliances may be a way of collectively dealing with some structural change in the industry. Finally, firms may be using alliances to project an image of legitimacy in their industry.

Two important features emerge within such initiated alliances. One is that there is no third party involvement. The other is that trust plays a significant role in such practices. As the only actors involved in the cooperation, the organisation form of alliance may only depend on the partners, who decide what contractual form they think will best serve their interests. One factor which could determine the choice of organisational form is the relative dominance of each firm (Adobor 2006).

c). The third type of alliance is cooperation facilitated by the presence of a third party or a convenor (Adobor 2006). It is likely that most convenor-facilitated forms of collaboration will bring together multiple partners, and so the dominant organizing form should be network forms. Over time, the parties in a network may come to realise their interdependence and every party will realise where exactly they fit in the network.

d). The third party facilitator may be a government body, especially in non-market economies, which leads to the fourth type of alliance, where the active participation of government as third parties encourages or discourages alliances. Jaslow (1983) argues that most Chinese and East European alliances involve some government control in one form or another. Alliances that fall into this category are mainly joint ventures.

Collaboration and cooperation are alternative forms of interactions between alliance partners but the apparent similarity between the two may be part of the reason why many scholars treat the two concepts as synonymous. But Polenske (2004) holds that the concept of alliance seems too big a topic to successfully analyse. Therefore, he offered an alternative definition of collaboration. In his article, collaborative relationships are defined to *'include direct participation by two or more actors in designing, producing and /or marketing a product'*, whilst cooperation relationships are defined as when *'two* *or more actors agree through formal or informal arrangements to share information, support managerial and technical training, supply capital, and/ or provide market information'*. This generates a further criterion through which to test the relationship between collective alliances (including cooperation and collaboration) and competition. For example, those collaborative arrangements that require firms to perform in teams or to form partnerships usually take far longer to build than those cooperative ones that may just require firms to assist each other intentionally.

'Collaborative arrangements often lead to internal economies of scale, affecting the position of the firm on its long-run, average cost curve. In other words, by entering into a collaborative agreement, firms may expect to move to a lower position on their long-run, average cost curve' (Polenske, 2004). In contrast to collaborative agreements, cooperative arrangements often lead to *'external economies of scale, affecting the overall position and shape of the cost curve'*, helping a firm to reduce the average cost of producing at all scales of production. Firms frequently use these arrangements to lower their transaction costs. A cooperative arrangement differs from a collaborative one in that in the former firms may exchange information about research and development and product and process engineering, but each firm continues to work separately from the other.

2.3.3 Collaboration vs. Joint Ventures

In general, collaboration is regarded as one particular form of knowledge sharing joint venture, which may be configured in many different ways and associated with different kinds of behaviours. Buckley and Casson (1996) explored the strategic choice between joint ventures, licensing agreements and mergers using internalisation theory. In the model, they focused on a representative equity-based joint venture between two private firms. The knowledge provided by a firm may relate to a technology, or to market conditions. According to each firm's nature, both market expertise and technology could be shared. They classify the typology of joint ventures into three kinds, technology shared, marketing shared and both. Only the pure technology shared joint venture is defined as R&D collaboration. In the end, they claimed that *'if the market size is very small and the pace of technological change in the global economy (volatility) very high, then the null strategy will be chosen. As the market size increases and/or volatility falls, licensing is preferred instead'.* Collaboration is preferred when either market size or volatility are both low.

Zhang et al. (2007) also investigated the relationship between R&D intensity and international joint ventures (IJV). Data came from China's Third Industrial Census conducted in 1996, which included almost all the Chinese major industries. However, the authors only chose data from three industries, where the high-tech firms are mainly located. These included the electric machinery industry, the electronics and communication industry and the office equipment industry. Using regression analysis, the authors of paper conclude that R&D intensity has a positive relationship with IJV performance when the IJVs have an export market focus, but not when the IJVs have a local market focus. Specifically, results suggest that while IJVs with a local market focus may invest more in R&D activities, they are less able to benefit from R&D than are IJVs with an export market focus. However, as the balance of knowledge in IJVs involving developing countries and developed countries is very uneven between the partners it might be that the joint ventures of this kind are more akin to market access arrangements rather than technology development. Specifically, the advanced technology firm contributes state of the art innovation to his partner, whilst his partner opens access to the local market. As a reward, the technology supplier may even get majority ownership of the IJVs (Li, 2001; Liang et al, 2001). This leads us to hypothesise that the type of IJV covered in Zhang's article may best be classified as the license-spread type in Buckley and Casson's (1996) theory.

But slightly different to Zhang et al. (2007), Chen et al. (1999) suggest that joint ventures have no significant impact on innovation capability and that joint ventures influence a society's average technology level mainly through economies of scale rather than via upgrading technology generation.

In contrast, Luo (1997) advocates that IJVs may be divided into two groups according to the partner's selection criteria in the formation of the IJV: operation-related criteria or cooperation-related criterion. The first covers the strategic traits of partners, including absorptive capacity, market position and the degree of product differentiation, whilst the latter criteria concerns organisational traits, including collaboration, organisational form and size. Without strategic traits IJVs tend to be unstable, while without organisational traits IJVs tend to be unprofitable. In particular, by employing cross sectional data re Jiangsu Province in China from 1988 to 1991, the author reveals a significant positive relationship between collaboration and IJV performance such as growth in return on investment, local sales, export revenue and reduction in operational risk.

2.3.4 Why Collaborate in Innovation?

Given that there are many ways in which firms may collaborate in technology development, the next issue is to ask why firms may wish to collaborate in this way. Shaked and Sutton (1987) argued in an early paper that non-cooperative games may have collusion as a preferred outcome with firms preferring to collaborate rather than compete. This however still leaves open the question of what circumstance encourage firms to collaborate and what circumstances discourage them. Is it always best to collaborate whatever the circumstance? It is useful to separate out the literature into two parts: (i) first that which explains collaboration as the result of the solution to a game theoretic model; and (ii) other approaches.

2.3.4.1 Game Theoretic Approaches

There is a rich array of literatures involving game theoretic models of the relationship between innovation and imitation. Assuming Cournot or Bertrand equilibrium, one can examine with such models firms' best responses to changes in any factor of the game. Most models, especially early models, did not allow for collaboration but concentrated upon determining producers' optimal price-output strategy, technology differentiation, or best technology adoption time. We have discussed these above. Here we are more interested in such models that allow for collaboration.

Pepall (1997) investigates imitative competition in a two-stage game within a vertically product differentiated market. Two players enter the market sequentially. At the first stage, the leader chooses whether to enter the new market and incur a certain sunk cost. At the second stage, the follower decides how closely he copies the technology from his leader. Obviously, this results in an advantage for the follower, as its costs are lower the more closely it copies the innovator's product. But against the advantage is the drawback that the more similar their products are, the more intense is the degree of competition. Producers need to determine their best strategies according to this trade-off between imitation and differentiation. The author allows for the possibility of collusion after taking a strict patent policy into account. The paper finally suggests that all firms' strategies relate closely with consumers' income distribution. In particular, there is more incentive for the late entrant to imitate in a market that is wealthier and for income distributions that are either relatively poor and heterogeneous or relatively rich and homogeneous. A policy of tight patent law protects the innovator's profitability effectively rather than a policy of cooperative alliance. However, the author does not explicitly differentiate between collusion and collaboration. Moreover, it also seems that by maximizing industry payoff, both firms behave to jointly monopolise not only the latest technology, but also the whole market, which may be in breach of antitrust laws.

Another model is introduced by Greenlee & Cassiman (1999), who extend the model of d'Aspremont & Jacquemin (1988) to examine research joint ventures and collusion. As a first step, they investigate a bench mark model where firms collude in the competitive output market. In the following section, the firms are allowed to cooperate on either R&D level or output level or even both by forming a joint venture organisation. The conclusion suggests that the research joint venture may be only acceptable when the spillover effect is very large, whilst output collusion improves the profitability for all parties only when allowing a high possibility of spillover and inexpensive cost reductions. There are still limitations. Firstly, the technology they explored is for cost reducing purposes, indicating that R&D in these models must refer to process innovation. They also assume that only a single homogenous good is available. In addition, product market collusion is against antitrust law and will face serious penalties in most economies (Brod & Shivakumar, 1997). All these problems should be more appropriately addressed.

It is of course apparent that antitrust laws consider collaboration in innovation and product market collusion as quite different. Technology cooperation is generally permitted by law, because, unlike market collusion that may undermine competition, the partners who cooperate in research will still be competitive in markets, and the level of social welfare will not be reduced by such behaviour. Moreover, as Baumol (1992) suggests, collusion may be worse than just reducing welfare, because collusion may generate waste that monopoly could avoid, while an unstable price cartel may carry heavy constriction and monitoring costs. In fact, antitrust enforcement generally distinguishes between 'good cooperation' and 'evil cooperation' according to the purpose of cooperation. If the aim of cooperation is to attempt to drive others out of the business by using, for instance, 'price fixing' (Baumol, 1992), in order to establish monopoly power, such cooperation is forbidden. However, if the nature of cooperation is not 'predatory' but just leads to a price war so that firms compete by supplying cheaper or better quality products, then the cooperation is allowed. Thus, compared with collusion on output levels, cooperation on technology levels must be desirable (Samuelson, 1987).

Giannakas and Fulton (2005) develop a sequential three stage game-theoretic model of heterogeneous producers to examine price behaviour, market and welfare effects of cooperative involvement in process innovation activity in the agricultural sector. Their result shows that cooperative alliances could increase the arrival rate of innovations while reducing the price of agricultural inputs and the degree of product differentiation. Also, they find that cooperation does not decrease competitive capability.

Wang et al. (2005) explore the conditions encouraging resource sharing and maintaining collaboration in inter-organisational collaborative knowledge creation. They found the condition for the leader to collaborate is that its proportion of the marginal gain must be bigger than the unit investment elasticity, whilst followers are always willing to collaborate.

In contrast to leader's hesitation, Jiao (2007) suggested a different outcome. He employs both a cooperation game theoretical model and a case study to analyse spillover effects on collaboration in two, or more than two, player markets. Different from other previous simple game theory assumptions, the author addresses the heterogeneity of individual firm's natures, including their capability to raise funds, their technology and their market experience. The study shows that the technologically advanced firm always has an incentive to collaborate. But if the technology leader cannot make positive profit under self-innovation, the technology follower, his partner, may take the majority of the payoff under collaboration.

Similar deductions regarding the positive relationship between spillovers and collaboration may be found in the work by Cassiman & Veugelers (2002). They divide spillovers into two groups. One is the incoming spillover measuring the technology knowledge leaked from other firms, and the other is appropriability, reflecting the capability to capture innovation returns. By either investing in ‘absorbing capacity’ or trading knowledge with partners, firms should maximise the incoming spillover to increase the rate of technology invention. By using empirical data on Belgium, they found greater incoming spillover leads to a greater probability of collaboration, whilst higher appropriability results in a higher probability of vertical cooperation.

However, some scholars believe that regardless of technology advantage, both players must prefer collaboration under some circumstances. Tan (2007) discussed the spillover effect when a firm collaborates in a two stage-two firm game theoretical model. He claims that since collaboration significantly reduces the cost of adopting new technology, firms always have a greater incentive to collaborate than compete. In particular, when the product substitution index is relative small, the possibility of collaboration may increase. As a result, collaboration may take the place of self-innovation as the firms’ best strategy. Similarly, by building a game theoretical model, Gao and Pan (2007) reach a conclusion that firms in high-tech industry must prefer collaboration when players reach a Stackleberg equilibrium, although they do not take imitation costs into account.

Motta (1992) presents a partial equilibrium model with vertical product differentiation. Cournot competition and quality determined by R&D cost are assumed. He found that cooperative agreements had a positive effect on the amount of R&D undertaken, quality, output, welfare and potential entry. Very few firms choose not to collaborate only if the market is large and spillovers are not large.

Rosenkranz (1995) analysed a two stage, two player non-cooperative game, with vertical product differentiation. Firms determine both the date and the quality of their innovation. After the maximization of each firms' payoff, it is shown that at equilibrium, firms will enter the market sequentially. Also, there always exists a possibility of forming research joint ventures (RJVs) in R&D intensive markets, even in the absence of spillover effects and with stochastic R&D outcomes. This is because under competition, firms' expected payoff is normally lower than under collaboration. Binding contracts over innovation dates, quality or even side payments and splitting the post collaboration payoff, reduce uncertainty for at least one player. This then benefits both partners. However, this may lead to decreased social welfare and R&D underinvestment, and as such collaboration may not be desirable. But legal restrictions (such as on simultaneous entry) may increase the attractiveness of collaboration.

To the best our knowledge, there is currently no effective game theoretic model available which addresses at the same time both product innovation and collaboration and imitation in a dynamic market. As mentioned above, some literature focuses on the effect of both collaboration and imitation on process innovation, but ignores their influence on product innovation; whilst some work considers vertical product innovation but neglects collaboration and imitation. In addition, very little research explores the details of cost sharing under collaboration, whereas the optimal equilibrium cost sharing plan between partners, in particular, how the firm with the low technology level behaves is an important issue. These two problems are both explicitly explored in the game theory model developed below (Chapter 3). Using the predictions generated from that game theory model as a guide, the determinants of collaboration and collaboration cost in China are then further investigated empirically (in Section 5).

2.3.4.2 Other Approaches

The recent introduction of the idea of 'open innovation' may provide some insight into collaboration. Chesbrough (2003) defines the term, open innovation as *'a paradigm that assumes that firms can and should use external ideas as well as internal ideas, and internal and external paths to market, as the firms look to advance their technology'*. Since no one firm could possess all know-how, information and resources (Cassiman et al, 2009; Hamel & Prahalad, 1994), open innovation allows firms to acquire complementary resources or technologies which do not have to cross firm boundaries (through channels, such as licensing, R&D collaboration and company acquisition, Cassiman & Veugelers, 2006; Li, 2010). A skeptic may argue that choosing an open innovation strategy is merely a greedy way to embrace critical knowledge owned by others without giving up one's own. Others, however, may argue that such open collaboration is a wise way to test product compatibility with those of other firms, even when these firms are rivals (Hall & Rosenberg, 2010). For instance, it is crucial for pharmaceutical firms that the drug they invent works well with drugs produced by other firms. Similar cases may also be widely observed in the engineering or software industries. Open code (David & Ray, 2006) in the software industry, created among programmers to improve programming and accelerate software design, is another example, and considered as a typical collaborative effort.

Matsubayashi (2007) studies an instance of price and quality competition in the Japanese internet market. By observing 'perceived price' as the determinant of consumers purchase decisions in a two stage, two goods game, the author compares the payoffs to firms of two alternative strategies: product differentiation or vertical integration with a complementary firm. Compared to the vertical integration models of Economides (1999) with dual monopolists, here the model assumes the existence of three firms, two players downstream and one complementary monopolist supplier. The results show that vertical integration always has a positive effect compared with competition on firms' profit and consumers' welfare. A virtue of this model is that it distinguishes consumer characteristics from market differentiation preferences which is rare in the literature. However, a basic assumption in his model is that firms' natures at the beginning point are symmetric and homogeneous which limits the relevance of the conclusions.

This idea of a positive relationship between collaboration and firms' welfare (profits) is widely supported by many scholars (Baumol, 1992; Side, 1980; d'Aspremont & Jacquemin, 1988; Teece, 1986; Luo, 1997). The result shows that the necessary condition for firms' switching from competition to collaboration is a resultant growth in 'post-alliance payoffs' (Parkhe, 1993). Apart from maximizing net profit being one driving force, another important factor, as Rosenkranz (1995) mentioned, is reducing the cost of or risk attached to technological change (Baumol, 1992; Cassiman & Veugelers, 2002; Bellais & Guichard, 2006; Cassiman et al, 2009; Luo, 1997; Pennings & Harianto, 1992). In particular, when a firm attempts to reach out into unfamiliar industry, how to choose a partner to cope with costly development of technology intensive products becomes a trigger problem (Brockhoff, 1992).

Pisano (1990) provides an example of a case of collaboration for the purpose of cost saving. A pharmaceutical firm with a good reputation intends to introduce a technology intensive related medicine on to the market. He may either choose in-house innovation, so called vertically integration, or procure the R&D service from another biotechnology firm. If choosing in-house innovation, the firm could obviously capture the payoffs once the medicine is successfully commercialised. However, from the respect of product innovation cost, if the firm allows collaboration, the other firm may do the R&D more effectively at less cost, in which case, collaboration may be preferred to doing the R&D himself. Even though the case Pisano addressed in fact looks more like R&D outsourcing, it still inspires us that for some firms, their strategic preference may be significantly altered because of potential cost saving.

Contractor (1985) suggests that a joint venture firm could smooth out cash flow and diminish risk by three channels: sharing of equity and rent of parental firms, licensing agreements, and trade with parental firms. The first channel, sharing equity and rent of parental firms is particularly important. The problem is that most of the rents from technology transfer that are captured by the joint venture, are generated by either creating revenues from the introduction of new or improved technology, or reducing cost by importing a more efficient production process with knowledge intensive technology. This in fact includes all impacts that both product innovation and process innovation can make. Moreover, the author claims that in the joint venture organisation, the higher the rent desired by the technology leader, the greater proportion of cooperation cost that may be paid by the technology follower. To some extent, this deduction indicates that when a firm has to share technology information with a more advanced rival, it is probably difficult to make its voice heard.

Brod and Shivakumar (1997) also emphasised the choice of collaboration in terms of risk reduction. By extending the two stage game theory model of d'Aspremont and Jacquemin (1988), they not only allow product differentiation among a number of firms, but also offer a comprehensive welfare comparison. Their analysis makes two points. First, because of the sharing of collaboration cost and uncertainty, regardless of the firms' performance in the product market, cooperative R&D is always better than non-cooperative R&D. Second, firms that cooperate on output levels as well as on the R&D level could capture greater payoffs than those that cooperate on R&D alone, even though such activity may be prohibited by antitrust law.

Moreover, it seems that whether firms collaborate is also related to the scale of product sales (Li, 2010). Buckley and Casson (1996) suggested that globalisation is relevant to the joint venture ownership of production. With global markets and updating production facilities in mind, a firm is always trying to participate in a lower transport cost game to maximise the opportunity for exploiting economies of scale in production. This requires an ideal geographical distribution of its demand, which may lead to technological collaboration between a leading firm and a local firm. As high-tech firms may make a series of market-access alliances with firms in different localities, this gives the high-tech firms more experiences in joint ventures. In particular, the greater the fixed costs of R&D, and the greater the economies of scale in production, the more important is the marketing synthesis in achieving the critical level of global sales. Global sustainable competitive advantage as a reason for collaboration is also stressed by Zhang et al (2007) and Feng & Chen (2004). Chen (2007) has also emphasised that that R&D investment in overseas subsidiaries can help multinational corporations (MNCs) exploit their firm-specific resources to suit local markets better.

Love & Roper (2004) argue that the aim of collaboration may differ according to market type and institutional and social norms. After analysing the data obtained from the Product Development Survey (1991 to 1993), it is argued that the reason German plants collaborate is for cost sharing and risk reduction, whilst most UK firms choose collaboration in order to achieve an acceleration of innovation development. That is probably because compared with the UK market, the German institutional context allows German innovation to focus more on diversified quality production and incremental customisation rather than radical and sporadic innovation with a relatively opportunistic approach.

Similarly recent organisation studies (e.g. Gao & Pan, 2007) suggest that the incentives to collaborate may be affected by different management mechanisms. They argue that trust mechanisms, knowledge-sharing mechanisms, group technology diffusion mechanisms, communication mechanisms and group reputation mechanisms will all impact significantly upon the extent of collaboration. Hill (1990) also emphasises the importance of trust. Despite finding that, in game theoretic models, collaboration is often preferred to competition, difficulties in building trust and reputation may well deter collaboration. Highly uncertain outcomes, or the paradox when opportunistic rent obtained from the current period outweighs the future payoff from collaboration, may also result in cooperation instability (Parkhe, 1993). The most common factor affecting the stability of collaboration is payoff revaluation. As Hennart (1991) suggested, if firms realise their patterns of payoff may change, then the decision to collaborate may be reconsidered. Parkhe (1993) used a prisoner's dilemma game to explain this. In a game, two players who are suspected to have committed a serious crime, are questioned separately without knowing the other's decision. If the suspect comes to value the payoff of cooperation more than squealing because of his reputation, he may choose mutual cooperation rather than unilateral defection, thus turning the game into a Stag Hunt. Or, if the suspect believes that mutual cooperation would weaken his competitive position in the future, he would probably reckon on a higher payoff from mutual defection, leading the game to Deadlock.

Parkhe (1993) also argues that the shadow of the future may affect the stability of collaboration, with claims that future payoffs casts a shadow back to the present. If defection occurs, the other player may take retaliatory action. A 'Tit for Tat' strategy, on one hand, forces players to move rationally and carefully taking initial steps with great caution. However, on the other hand, it also results in a possibility that once collaboration collapses, the organisation rarely reverts to its original status. It is suggested, the greater is the degree of cooperation between firms, the longer will be the shadow of the future. Since frequent interactions, high transparency, and long-time horizons may help cooperation to be more stable, this consequently makes the nexus between present and future decisions even closer. Parkhe thus suggests that the longer two players collaborate, the longer the shadow of the future. But that deduction is only for a market with perfect information, where cheating could be observed without a time lag.

Last but not least, latest research reveals that reasons beyond market characteristics could also influence the decision to become involved in strategic alliance. Krucken et al (2007), for instance, examines technology transfer in Germany and US in respect of the growth of emerging innovations. They discusses the two country case by respectively employing three different models, the information and documentation model, the cooperation model and the blurring of boundaries model. Interestingly, they observed a phenomenon that the innovation network (collaboration) embedded in university-industry relationship is significantly more visible in Germany than US. One possible explanation is that in Germany, European Community research funding, may well encourage firms to participate in networks with firms in other European countries. Another possibility is the cultural tradition of collaboration in Germany is relatively more encouraging.

Empirically, even though we notice that collaboration has been more studied in the literature over the past two decades, there are still many examples of firms that prefer not to collaborate, or where firms attempted to collaborate but have finally failed to do so (Brod & Shivakumar, 1997). Moreover, it seems that, even in situations where firms capture high payoffs to collaboration, some of the technology alliances still do not last long. Empirical evidence shows that up to 70% of collaborations collapse (Parkhe, 1993; Geringer & Hebert, 1991; Man & Duysters, 2005) and two thirds of all alliances experience severe leadership and finance problems in the early stages of collaboration (Bronder & Pritzl, 1992).

2.3.5 Collaboration and Intellectual Property Rights

As is obvious, technological knowledge may have to be (must be) shared during the collaboration process i.e. there must be technology transfer (not only from one party to others, but also probably from scientific research to applied technology in practice). This creates particular problems in collaboration, (Fiedler & Welpe, 2010; Gans & Stern, 2003; Hung & Chu, 2006). On one hand, the innovators are attracted by the specific rewards to be derived from jointly developed technology, whilst on the other hand, they also have severe concerns about 'free rides', or misappropriation of knowledge by collaborators (Samuelson, 1987). As Schroder (2005) claimed, there is no doubt that free rides on the inventions of others must happen in a market without proper intellectual property rights (IPR) protection - the only question is when.

Intellectual property rights protection is defined by the US Congress as the means to *'promote the progress of science and useful arts, by securing for limited times to authors and inventors the exclusive right to their respective writings and discoveries'*. The range of IPR protection in fact is very broad, including *'anything under the sun that is made by man'* (David & Ray, 2006). In practice, such protection normally is operated by intellectual property laws, including the laws of patents, copyright and trademarks or service marks (Samuelson, 1987). They are respectively focusing on different fields or purposes, which cover areas from manufacturing, to culture, to commercial trade (Brown, 1997). In manufacturing, for instance, the intellectual property law (patents) protects the inventor or creator of new technology against free riders who would reduce the return to innovation and discourage its development.

Some researchers (Teece, 1988; Cassiman & Veugelers, 2002) observe one important reason why firms that are technologically first are not real winners is that they could not commercialise the innovation successfully because their IPR is weak. They refer to this phenomenon as weak appropriability, indicating limited efficacy of the legal mechanisms of protection. If IPR is not fully protected, plenty of patents may be 'invented around' at lower cost. There will then be doubts as to whether the monopoly rents from innovation may fully be obtained.

Teece (1986) further explains the failure of innovation commercialisation by the impact of complementary assets. He argues that when IPR is weak, the role of ownership of complementary assets played in innovation may be even greater than the development of intellectual property. Losing control of certain complementary assets may result in profits flowing from innovator to imitator and consequently making the innovation fail. Therefore, control of the co-specialised assets appears vital for survival in the long run in a market with weak appropriability.

In fact, according to the data from Intellectual Property Section of United States Department of Justice, the annual loss from IPR infringement suffered by U.S. firms from mid 1980s to 2005 has increased from 60 billion to 250 billion dollars (Helpman, 1993; http://www.cybercrime.gov, 2011). And that figure has been widely agreed to have considerably increased by now. In particular, it is believed that about 5% to 7% of world trade is in counterfeit goods, representing about $512 billion of global sales. Besides, the loss suffered from infringement not only covers counterfeit goods, but also includes products in violation of patented technology, copyrights, or trademarks. The report shows that infringement of copyright alone causes up to $35 billion losses to U.S. companies in 2005. This severe situation may justify further IPR protection.

A common argument about IPR is that tighter IPR may discourage innovation by some parties. Some research suggests that tighter IPR can only benefit large firms with monopoly power in developed countries. Since the amount of technology transfer reduces significantly as IPR tightens, the players in developing countries, such as India or Brazil may suffer from tighter IPR (Helpman, 1993). He claimed that whether tighter IPR encourages net welfare for all depends upon the degree of imitation. Since tighter IPR shifts product lines from developing countries/ firms to developed countries/ firms, in the face of tighter IPR, demand must diminish in developing countries/ firms, whilst growing in developed countries/ firms. In contrast, shifting the production line will also mean moving production to a higher expenditure region with higher labor cost and higher operational cost. This conflict leads to a greater product price, which may reduce demand in both regions/ firms. Thus, to sum up, strict IPR must discourage innovations in developing countries/ firms, whilst the effect of tighter IPR in developed countries/ firms depends on the trade-off between those two points mentioned above. In particular, the negative effect caused by tighter IPR is maximized in a region with a higher imitation rate. If that happens, the developed countries/ firms may benefit more from receiving additional rent from developing countries/ firms rather than loss of profit by lifting product price. Therefore in general, the developed countries/ firms must prefer tighter IPR whilst the developing countries/ firms prefer looser IPR.

Meanwhile, it is clear that even when tighter IPR is provided, there still exists uncertainty and ambiguity of value capture and value estimation on invention during the process of technology transfer (Fiedler & Welpe, 2010). For example, the problem that firms rarely obtain all the returns from innovation exists even in the US market, which is commonly recognised as the strongest economy in the world (Bellais & Guichard, 2006). However, it could be argued that regardless of the strength of IPR protection, technology may gradually flow from the inventor to his rivals through use of the same upstream suppliers (Design News, 2004).

Moreover, it seems that the effectiveness of IPR also varies with the nature of research. Bellais & Guichard (2006) investigated the spin-off experience in UK technology transferred from defence to the civil sector. They found the interest in commercialising defence innovation from lab to market is not strong, even though proper IPR protection has been granted.

Spillovers, as another example, may be generated through formal or informal channels from various types of alliance, such as collaboration, cooperation, outsourcing or joint venture. As Greenlee & Cassiman (1999) state, *'the fruits of R&D are a public good'*, indicating that the spillover effects stimulate the availability of invented knowledge. Collaboration on R&D may actually relax the problem of public goods and lead to higher spillover effects, Collaboration may thus exacerbate the free rider problem, Some people claim however, that collaboration helps to better utilise the IPR protection and to increase the capability to capture the rents of invention, by internalising the externalities or improving the appropriability of R&D (Greenlee & Cassiman, 1999; Brod & Shivakumar, 1997; Kogut, 1988).

Most people believe that it is IPR that makes technology transfer possible (Bellais & Guichard, 2006). Love & Roper (2004) advocate that to cope with the problem of leaking knowledge in a market with weak appropriability, firms could either collaborate or subcontract to better protect the IPR. Pepall (1997) investigates imitative competition in a two-stage game in a vertically product differentiated market. The author also detects the possibility of collusion after taking tight patent policy into account. The result indicates that tighter IPR protects the innovator's profitability more effectively than a policy of cooperative alliance. The problem in this work, however, is that the author did not explicitly distinguish between collaboration on technology and cooperation on product output, leaving confusion and debate regarding the impact of IPR on strategic alliances.

Gans et al. (2002) suggest that, instead of competition, more efficient cooperation may be achieved by firms in a market with strong IPR, low transaction cost and potential partners with complementary resources. Since the tight patent protection lowers the possibility of a free ride using or producing the technology, and complementary resources offer a higher chance to exploit the know-how owned by other firms, they found, regardless of the firm size, that the inventor controlling IPR always prefers to pursue a cooperative strategy when commercialising the technology.

Similar conclusions are reached by Schroder (2005) who believes the IPR works on collaboration indirectly through transaction cost. Tighter IPR ensures a lower transaction cost, which consequently increases the firms' payoff post collaboration. Thus, stronger IPR stimulates the collaborative incentives and increases the possibility of success in collaboration by avoiding external predation. Employing Belgian manufacturing data from the Community Innovation Survey in 1993, Cassiman & Veugelers (2006) also suggest that tighter IPR may push firms to *buy* technology though external R&D instead of *making* it by internal R&D.

The latest empirical research by Fiedler & Welpe (2010) suggests that the relationship between IPR and collaboration depends on firm size. By employing survey data on the German nanotechnology industry from 2005 to 2006, they examined if IPR, transaction cost and complementary resources play an important role when firms cooperate. The result shows that for small and medium firms (SME) the positive influence of low transaction cost and complementary resources confirm the conventional ideas that both factors may stimulate cooperation incentives, whilst for the large firms, interestingly, both IPR and complementary resources have negative impacts on the cooperation decision. This is probably because firstly, larger firms own richer know-how and greater resources, and have less need to 'seek around' as much as SMEs. Secondly, with the emerging nature of the nanotechnology industry there are many unknown players and undefined applications and it may be difficult to locate a particular partner.

We have very little information upon the importance of IPR on collaborative agreements in China. In fact in most developing countries, the enforcement of IPR may be particularly difficult. With limited education, infringement is sometimes not even assumed prohibited. In China, for instance, the record shows that the first IPR training centre was not established until 1996, almost 14 years after the Chinese intellectual property laws were drafted (http://en.wikipedia.org, 2011). If there is weak IPR protection, the design of the contract which guarantees the sharing of payoffs from collaboration seems particularly crucial (Bellais & Guichard, 2006). This will obviously impact upon factors relating to the formation of an alliance, such as negotiation, communication, bargaining and evaluation of the expected technology.

2.3.6 Collaboration and Transaction Costs

Transaction cost theory emerged in the 1980s as an alternative means of analysing firm level strategy in the process of technology transfer in terms of cost. According to Winebrake (1992) and Bellais & Guichard (2006), technology transfer can be defined as *'the process by which technology, knowledge, and/ or information developed in one organization, one area, or for one purpose is applied and utilised in another organization, in another area, or for other purpose'*. Following the influential research on transaction costs in organisations by Williamson (1985), Hill (1990) clearly suggests the idea of transaction cost in his work: *'The cost of negotiating, monitoring, and enforcing a contingent claims contract to ensure against opportunism are called transaction cost'*. He claims that due to the existence of opportunism inherent in technology transfer, transaction costs reach their lowest level only when players cooperate and fully trust each other. Consequently, firm-level payoffs are maximized only when firms transfer technology via collaboration rather than via the market. Then, even if a market reaches a competitive equilibrium, for those players who are not currently cooperative, there is an incentive in the long run to cooperate. That is because first, the market has a self-selection mechanism to remove most opportunism and, second, the nature of the transfer mechanism requires complementary complex and substantial modifications for better commercialising technology. In particular, for technology transfer from basic research to a customer aimed markets (Bellais & Guichard, 2006), in-depth 'co-development' is necessary. Therefore, in the long run, technological cooperation may come to dominate the market. As transaction costs reduce opportunism, most researchers suggest a negative relationship between transaction cost and the success of collaboration. That is to say, the higher is transaction cost the lower will be the success of, or the fewer collaborations there will be.

Brockhoff (1992) investigates 385 of the largest firms in Germany by questionnaire regarding various aspects of R&D cooperation. In a sample of 135 firms which eventually responded as collaborating, 60 firms explicitly agreed that high cost of negotiations and transactions is disadvantageous to R&D cooperation. In addition using a Chi-square test, a correlation between a low level of collaboration success and high transaction cost frequency was found. In particular, if firms were forced to collaborate in R&D by government (or other unforeseen reasons) it led to less success and higher transaction cost.

Yet opportunism is almost inevitable (Brockhoff, 1992). Since opportunism is human nature (Parkhe, 1993), there is no perfect way to avoid it. Thus monitoring partner's behaviour may use up some of the potential payoffs to collaboration. However, a possible way to reduce transaction cost is by building or improving trust within strategic alliance organisations.

Generally speaking, trust would be related to past experience, reward incentive structures and reliance upon third parties. Firstly, the more information of past experience players have, the more chance there is to better understand mutual needs and instantly adjust in response to partners' action (Ford, 1980; White, 2005). The information of past experience not only means the collaboration experience with firm itself, but also includes collaboration reputation with other firms (Bolton et al, 2005). In particular, in some industries, heavy investment with higher exit barriers and greater dependence may imply a relatively long-term commitment (Heide & John, 1990; Mehta et al, 2006). The feedback of such long-term commitment will then help to better understand partners' real needs through strategic alliance. This point of view is also supported by Brockhoff (1992), who believes that the experience of R&D cooperation between universities/ research institutions and private firms may significantly reduce uncertainty in the technology transfer.

Secondly, stimulation of expected rewards, provides the player with more effective safeguards, which allows the agreement to be fulfilled (Pearce, 1997), and to cope with perceived opportunistic behaviour.

Last but not least, increasing the closeness of the relationship may also stimulate the growth of trust. This idea was similar to what was mentioned by Mehta et al (2006) who suggested that building trust looks like making friends. On one hand, we intend to trust an old friend, whilst on the other hand, we are also likely to believe a close friend. As a result, to avoid being unilaterally abandoned by alliance partners, investing in high sunk cost non-recoverable assets is a wise choice, for this commitment closely binds partners on a shared goal and the value of non-recoverable assets would significantly reduce if the strategic alliance collapsed. Such non-recoverable assets may also be labelled as complementary assets or specialized assets in the literature. Teece (1988) suggests that since the specialized assets are not easily available in an industry, they become critically important in appropriating monopoly rents from innovation. In particular, when a regime of weak appropriability applies, the irreversibility of complementary assets is relatively even more vital than being the first to introduce the technology. To some extent, it looks more like a gamble, however, that is indeed an effective way to increase trust and diminish opportunism (Smith & Aldrich, 1991).

However, Pearce (1997) also suggests that to reduce opportunism, firms' focus on post-collaboration alone is just not enough. In particular, he instead believes that the major component of transaction cost is bargaining cost or the cost of negotiating through the technology transfer. The bargaining cost he defined is the cost that leads to an agreement to form an alliance. All this could only occur before the formation of alliance. Once the collaboration is established, the organisation would not be affected by the bargaining cost anymore. The overall level of uncertainty in the ex (pre)-collaboration period may be caused by imperfect communication, lack of trust, difficulty in verifying collaboration performance or resource (including technology resource and human resource) distribution, and conflicts of specific contract terms. In particular, the bargaining cost will be influenced by the political environment within the Top Management Team (TMT) and could dramatically determine the realisation of the goals in (post) ex-collaboration period.

Transaction costs help to reduce uncertainty in both the pre-collaboration period and the post-collaboration period. The only question is how to balance the transaction cost over the technological life cycle. As the transaction cost occurring pre-collaboration mainly concerns the negotiation between partners to commit resources, some people suggest it may involve higher uncertainty than transaction cost incurred monitoring defection or protecting joint patents post-collaboration (Bronder & Pritzl, 1992). Yet empirical studies show that in some cases, transaction cost is at a higher level in both early and late stages, but at a lower level in the intermediate stage, which indicates a U shape relationship between the transaction cost and technology transfer uncertainty (Brockhoff, 1992).

2.3.7 Collaboration and Strategic Management

Strategic management theory deals with a set of leadership centred activities that enhance firms' performance via detection and evaluation of its internal and external resources (Siegel & Tuckel, 1985). It was initially developed from strategic planning which mainly concerns the activities associated with the collection and utilisation of external environmental information. Instead of continuity in the environment in strategic planning, strategic management assumes the likelihood of discontinuity and surprise (Klay, 1991). The evaluation and control of the information gathered from rivals or related industries and the success of its on-going projects is crucially important in strategic management. Feedbacks from the analysis of market situations allow the leaders of organisations to decide whether the implementation of current strategy is adequate and whether/when to replace it by a new strategy. This may result from the need to meet different market circumstances (Ansoff, 1984), which may be caused by introduction of new technology, new rival, new product or new policy (Lamb, 1984). This indicates that the optimal strategy may constantly vary from time to time. As addressed by Klay (1991), *'Success is defined as the implementation of adequate strategy, not the development of perfect strategy'*.

A model presented by Johnson et al (2008) gives us an answer on how to evaluate the adequacy of implementation of a strategy. In their research, they listed three key success criteria, suitability, feasibility and acceptability, explaining the three questions respectively as 'would it work?', 'can it be made to work?' and 'will it work?'. By using their classification, we look at the literature on strategic management to see how collaboration might occur in firms.

The first criterion, suitability, describes whether the strategy is economically reasonable in terms of environment and capabilities. Bronder & Pritzl (1992) believe increasing competition and technology breakthroughs result in collaboration, which may allow the firm to better adapt in global markets. As firms are no longer an integrated unit of value chains, forming a network associated with operative cooperation and technology collaboration might be a wise choice. The European aerospace alliance, Airbus, formed in 1965, is a typical example of core competencies integration by European civil aircraft companies in order to compete against their common rivals, the American market leader, Boeing and McDonnell Douglas. Another example of a strategic alliance may be found between drug companies, Bayer Health Care AG and Millennium Pharmaceuticals in the biotech industry (Ziegelbauer & Farquhar, 2004). The goal of their collaboration is to beat other common rivals on time scale so that they could be first to patent partial DNA sequences and dominate the access to potential drugs discoveries. The area of cooperation/ collaboration does not only cover collaboration in technology, but also includes product development, service and operation management. The main purpose of the alliance therefore is to jointly compete with the dominant firms and greatly expand market share.

Besides, collaboration may also lead to greater mutual learning capability and continuous adaption (Parkhe, 1991; Bronder & Pritzl, 1992; Hult & Ferrell, 1997). Here, the term 'learning' may be read as defined by Cohen and Levinthal (1990) as *'the ability to recognize the value of new external knowledge,* *assimilate it, and apply it to commercial ends'*. In an article discussing the existence of a common European approach to management and knowledge transfer between collaborative companies, Lubatkin & Floyd (1997) claim that the firm leaders and middle managers must be familiar with know-what, know-how and know-why about the strategy they are going to launch. Indeed, pre-scanning of market position may help them to satisfy the three criteria listed above, but mutual learning seems to offer a better opportunity that greatly improves understanding. A similar conclusion, that learning orientation is one of key factors of successful collaboration, may be obtained from Mehta et al (2006), who investigated determinants of strategic alliances in international distribution channels. By employing manufacturing data from the US, Finland, China and Poland, their empirical results show that a partner with learning orientation is more likely to lead in a successful collaboration in the long run.

We have to note that different from other financial or physical resources, knowledge tends to be duplicable. On one hand, knowledge could transfer from donor to recipient, but on the other hand, the transformation itself does not diminish the amount of knowledge held by the donor. As addressed by Carayannis et al (2000), knowledge sharing might be considered as a positive-sum game. Moreover, Carayannis (1994) also advocates that learning at the level of organisational structure may lead to more radical innovation, called *'the cone of strategic technological hyperlearning'*. This 'learning-how-to-learn' effect reveals that knowledge sharing between firms may enhance their common knowledge and make it transferrable to some other specific valuable projects. Evidence supports the view that in the long term, the exchange of expertise and knowledge between partners may greatly enhance exploitation of opportunities in the market. Programmes such as EUREKA or HDTV supported by the European Community are a good example that firms have start to combine their know-how and to stimulate complementary competencies.

The second criterion, feasibility, actually concerns whether the resources required to implement the strategy are available. To answer this question in the case of collaboration, we may divide the problem into two parts: whether the strategy of collaboration can obtain resources which may not be available in the absence of collaboration; and is collaboration a comparatively cost effective strategy?

Some literature on strategic management answers the former conjecture positively, (the so called obstacles related to resource approach, see Cassimann & Veugelers, 2002; Barge-Gil, 2010). Bronder & Pritzl (1992) claim that apart from market potential and human potential, finance potential is also important. Collaborating firms could enhance their competitive advantages by gaining access to extra external finance support (Leonard-Barton, 1995). In recent years, consideration of university-industry or government-industry or even firm-to-state organisation also supports the idea that collaboration is an effective way to achieve complementary resources. In addition, diversified complementary resources from collaboration may form 'social capital' as a basis for market success. Fuller-Love & Cooper (1996), for instance, show that cooperation among different health care providers on IT resources may significantly increase competitiveness of hospitals and patient care. Carayannis et al (2000), focused on collaboration in form of government-university-industry (GUI) in the US, Germany and France. Their results show government, universities and industry may respectively supply adequate resources, such as policy, intelligence and funding to members of the organisation alliance.

However, other research tends to emphasis the costs of collaborative research. Narula (2004) claims that developing new technology internally is too expensive and collaboration might be more cost effective. Case studies by Fuller-Love & Cooper (1996) suggest that collaboration may enhance the cost efficiency of research by providing rapid and better management information.

The last criterion, acceptability, concerns the expectation of success in strategy and how feedback is to be identified by the firm’s leaders, stakeholders, employees and customers. This question mainly concerns three aspects: Firstly, in terms of firm’s leader and stakeholders, whether the corresponding return and the risk of failure (including product failure, market failure and management failure) might increase after adopting the collaboration strategy; secondly, in terms of firm’s leader and stakeholders, whether the administrative heritage will significantly change and whether it has unique preferences over firm’s collaborating; and thirdly, in terms of firm’s employees and customers, whether the firm’s culture will change and whether that change actually fits.

As there is already a rich array of literature about the first sub question, regarding the return and risk when firms involve themselves in collaboration (section 2.3.4), to avoid unnecessary duplication, we only consider the latter two concerns. The second sub question concerns whether collaboration interacts with the administrative heritage in firms, which, in fact, naturally leads us to another issue, how to select the right collaborative partner. Employing case studies of German and French companies, Lubatkin & Floyd (1997) analysed whether the form of collaboration varies across national boundaries. Their results reveal that managers from French companies prefer to collaborate with firms having a strong concept of management, whilst the managers from German companies like to work in a team with a comparatively loose management heritage. The reason why greater acceptance of power distance may affect managers' preferences in collaboration may be explained by the argument that, since everyone has a rightful place, firms with a French pyramid management structural heritage are easy to control, whilst German firms blurring the distinction between managers and workers may reflect and improve workers feedback rapidly and efficiently (Laurent, 1983). Therefore, when firms collaborate, French style firms like to collaborate with French style firms, whilst German style firms prefer German style firms. As White & Lui (2005) addressed, *'lack of willingness to adapt to each other's work styles will be correlated with managers reporting greater time and effort to work with an alliance partner'*. Therefore, to collaborate with similar management concepts helps firms to lower the transaction cost and continue the previous administrative heritage, which results in higher acceptability of new partner and greater success rate of collaboration.

The last criterion of concern, acceptability, i.e. whether the post collaboration culture fits, actually reflects another side of the partner selection problem from the view of employees and customers. Bronder & Pritzl (1992) suggest that the partner selection issue may be influenced by seven orientations, environmental orientation, international orientation, customer orientation, technology orientation, innovation orientation, cost orientation, quality orientation and employee orientation. Instead of a unique influence, these orientations may jointly affect the way one partner learns from another, even though the main purpose of collaboration is focused on technology development. On the other hand, as the workload grows after signing a collaboration contract, cultural conflicts are bound to increase over time. To cope with this problem, some commentators believe face to face meetings to be effective (Ziegelbauer & Farquhar, 2004), whilst others suggest that increasing the time scale of collaboration may greatly help (Brockhoff, 1992). Additionally, in recent years, people have preferred to distinguish this problem according to the types and intensity of cultural conflicts. Carayannis et al (2000), for instance, advocate that light culture conflicts may not always have a negative effect but may even stimulate collaboration. But, if the intensity of conflict between different cultures increases above a certain level, it may alter the strategic preference and result in the failure of collaboration. However, no matter how partners tackle the cultural conflicts arising from collaboration, the outcomes when different culture meet must be one of following possibilities: cultural pluralism, cultural assimilation, cultural transfer and cultural resistance (Buono & Bowditch, 1989; Bronder & Pritzl, 1992).

To summarise, apparently, the success of collaboration in the strategic management literature must involve the three criteria listed above, but the orientation firms choose may vary from case to case. Bronder & Pritzl (1992), for instance, suggest the motives for collaboration depends upon market type. In emerging markets, firms emphasise factor suitability and gaining access to core competencies, whilst in well-developed industries, firms prefer to succeed through finding better feasibility, focusing on the cost effective objective. Similar deductions may be found from Mehta et al (2006) who claimed that, different from the experience in developed countries, suitability seems to be especially important in developing countries. Strong relationships could be observed between learning orientation and cooperation in Chinese data. In contrast, Lubatkin & Floyd (1997) advocate that firms with a strong concept of heritage may be more market and differentiation oriented, whilst firms with a relatively loose heritage are more operationally and technically orientated. Similar deductions could also be drawn from Ziegelbauer and Farquhar (2004) who claimed that collaboration is more likely to succeed when key executives are committed to work closely with scientists, research management and other parties.

2.3.8 Collaboration and Product Market Competition

Is there any connection between research collaboration and product market competition? Do collaboration and/ or cooperation help a firm attain a competitive advantage over other firms? How do these relationships constrain or enhance local, national and global networks of firms? As collaboration and competition occupy two sub-branches in the strategic map respectively, these questions are crucial for generating a firm decision equilibrium model.

Snidal (1986) suggested that numbers per se should not necessarily reduce cooperation, because of shared risk with a popular project. But on the other hand, a rich array of scholars holds the opposite view on this issue. Polenske (2004) tried to answer the above questions by distinguishing definitions of collaboration and cooperation and building three different models labelled: the Italian model, the Japanese model and the Global model. He found close linkages among cooperation, collaboration and competition (3C), and suggested successful strategies for different industrial organisations. However, he did not indicate any positive or negative effects between the 3C. In his paper, the best strategy for small firms that innovate is to choose cooperation of the Italian type with short linkages between cooperation and competition. Collaborative arrangements in the Italian model might exist, but they have less influence on the competitive behaviour of the firms. The Japanese model, with the closest link in the uneasy triangle between collaboration and competition, is suitable for those medium sized firms which prefer collaborative mechanisms for risk sharing. Last but not least, large, especially multinational firms practicing collaborative behaviour globally may match the global model. The global model has two uneasy triangles. The first, like that of the Japanese model, with a close collaboration-competition link, represents the headquarters situation. The second triangle for the global model represents the behaviour for the part of the firm located in the peripheral regions, where neither collaboration nor cooperation occurs to any significant extent.

Different from Polenske (2004), some scholars pay attention to the effects on collaboration of the number of competing firms. Game theorists have studied the phenomenon of getting multiple participants to cooperate. Some argue that the prospects of cooperation diminish as the number of players increase (Oye, 1986). Coleman (1990) tries to give an explanation of this problem. *'If a number of person's interests are satisfied by the same outcome and if the benefits that each experience from his own actions that contribute to the outcome is less than the costs of these actions, he will not contribute if he is rational. If others contribute, he will experience the benefits of the outcome without incurring costs. If others do not contribute, his own costs will outweigh his benefits.'*

Recent research (Cassiman et al, 2009) advocates the idea that collaboration and competition may go hand in hand when firms invent. They explore balances and trade-offs on both collaboration and competition in respect of R&D, through three different aspects, project knowledge attributes, project governance structure, and project partner selection. In particular, R&D in collaboration is considered as a value creation process, with R&D in competition referred to as a value capture process. This is probably because it might be difficult to control the uncertainty inherited in technology transfer. By utilising the project level R&D data in STMicroelectronics from 1998 to 2003, the quantitative case study model they employed reveals that collaboration mostly occurs in basic research and with easily transferable projects. The result also suggests that collaboration is as important as competition because by pursuing both one may co-create value and capture value.

2.3.9 Collaboration and Innovation

Do alliances stimulate innovation in the competitive world? How does it work? Are there any variables which influence such results?

Various studies have observed that close inter-firm collaborations have positive effects on a firm's innovative activity. Baumol (1992) suggests that due to cost sharing, collaboration may stimulate innovation. Even if it does not, since collaboration is one way of information exchange, it helps the new technology to attain more widespread utilisation, which is welfare improving. Similarly, Womack et al. (1991) advocate that collaboration can not only accelerate innovation, but may also enhance informational advantages in industries.

Man & Duysters (2005) selected 30 papers on alliances and analysed the effects of M&A and alliances on innovation and the relationship between alliance and innovation. After careful modelling, 73% of hypotheses tested showed positive results. The results imply that alliances increase innovation. A number of reasons may explain why this happens.

> '*Firstly, cooperative agreements can ease a number of transactional and contractual differences (Williamson, 1975, 1985; Hennart, 1988; Jarillo, 1988).Secondly… the lower risk of large research projects and the integration of complementary knowledge may also increase innovation through alliances'. Furthermore… collaboration may also lead to a significant reduction in lead times in some particular industries. In high-tech markets where prices sometimes decline by more than 30% a year, it is obvious that the ability to bring products to the market more rapidly can offer a significant competitive advantage'.*

Similar to Man & Duysters, Guan et al. (2005) use a Chinese industrial database on 950 industrial enterprises, and find a positive relationship between innovation performance and collaboration among industry, research institutes and universities. In other words, the more collaboration the greater is technology innovation.

In particular, latest research specifies a positive relationship between collaboration and innovation. Faems et al. (2005) conducted an empirical study to examine whether inter-organisational collaboration supports the effectiveness of innovation activities. Belgian manufacturing firm level data are collected from the CIS for this purpose. In that study, a positive link between inter-organisational collaboration and innovation performance is finally revealed by Tobit models. As we addressed before, a possible explanation may be that collaboration leads to an increase in knowledge and a reduction in research cost and associated research risk.

Patrakosol & Olson (2007) collected longitudinal data from 23 top IT firms across 9 years and used a Hierarchical Linear Model framework to investigate changes in the innovation process. They divided innovation improvements into two groups: evolutionary improvement and revolutionary improvement. Evolutionary improvement occurs when the innovation process changes are incremental and gradual, whilst revolutionary improvement occurs when the process is radical and changed rapidly. In contrast to the statement by Baumol (2005) that evolutionary breakthrough is provided by corporates, whilst revolutionary breakthrough comes from entrepreneurs, Patrakosol & Olson (2007) suggest that close inter-firm collaborations were associated with evolutionary but not revolutionary improvement. This indicates that the history of the IT firms had engaged in close inter-firm collaboration may go positively with the effect on IT innovations. In addition, they also claim that both firm size and inter-firm collaboration help firms achieve IT innovation. If a firm cannot grow bigger, then engaging in close inter-firm collaboration is an alternative to increased IT innovation.

In contrast, recent studies have started to explore the breadth and depth of cooperation in research activities and whether these impact upon innovation (Laursen & Salter, 2006). Barge-Gil (2010) compared cooperation-based innovators whose innovation mainly relied on cooperation with both internal and external resources, and the peripheral co-operators that mainly innovated via their own internal efforts. In this article, the former cooperation type in fact was identified as the same as the open innovation model (Chesbrough, 2003), allowing for multiple channels of cooperation, such as licensing as well as collaboration; whilst the later model mainly refers to self-innovation with non-adopted external information. The author explored the impact of cooperation determinants upon the nature of cooperation itself and in particular, whether more cooperative effort could be devoted to collaboration. After analysing

Spanish CIS manufacturing data from 2002- 2004, the results suggest that there are both peripheral co-operators and cooperation-based innovators with fewer partners who may be seen as offering a greater depth of cooperation. However, most of the determinants of whether firms cooperate or not had little different impact upon the two groups, thereby suggesting that there might be no strong ties between cooperation and the ways of achieving it.

As to the question of whether powerful third parties influence the positive relationship between collaboration and innovation, Man & Duysters (2005) indicate that they do not. That is, any alliances involving public support or a public partner do not increase innovation, although they do lower the cost of innovation.

In contrast to the positive relationship between collaboration and innovation, only about 10% of selected papers indicate the opposite opinion. Some research indicating a negative relationship between alliances and innovation can also be found. One possible reason for an alliance to fail may be that partners in alliances are often competitors. Fear of helping a competitor to develop a new technology may be an incentive to hold back in cooperation (Cassiman et al, 2009). Mol (2005) and Barge-Gil (2010) also suggest that the collaboration decision may be affected by the fear of leakage of core innovation knowledge. Indeed, as Harrigan (1988) suggests, these may be the sort of situations in which *'good friends become enemies fast'*. However, Man & Duysters (2005) analyse the real reason why a non-positive relationship may emerge in some specific situations. They find that this tends to happen when the alliance is related to cost-saving objectives rather a new technology development process.

2.4 Conclusions

The literature reported above indicates that innovation and especially innovation and collaboration, covering issues of collaboration both between firms and firms, and between firms and state organisations, is a very live topic and an important one. In our game theory research below (chapter 3), we focus on collaboration between firms and firms. Then, using the predictions from the game theory model as a guide, we empirically explore issues of collaboration between both firms and firms, and firms and state organisations, although state organisations are much less subject to commercial pressures (Fuller-Love & Cooper, 1996).

The literature listed above indicates that collaboration does indeed impact significantly on firms' innovation decisions and then upon economic growth. The big questions are: when does collaboration occur?; what factors particular influence collaboration?; and does collaboration play a more important role than self-innovation? Two main streams of thought flow throughout the literature review above. The first concerns how to model firms' decisions upon innovation and collaboration. The second concerns what we know about innovation and collaboration in China. We start with the latter.

Although there is some empirical work available, most work upon the determinants and impacts of collaboration relates to the developed economies. There is little that applies to developing economies and to China particularly. However, the rapid growth and technological development of China make it an ideal test bed for study as well as a case study of enormous interest. Being a neglected topic and a matter of importance, it is our intention in the Chapters below to explore innovation and collaboration in China.

In order to do this empirically the research employs the latest panel data upon the Chinese manufacturing sector, incorporating the IT industry which is an industry with unique features exhibiting innovation and intense competition. The main strategy in the IT industry is centred on intellectual innovation, which is also a unique feature of high-tech industry in general. Unlike many other industries, IT innovations affect other businesses both internally and externally. Internally, they transform strategy and organisational structure; externally IT as a source of new ways of doing businesses when firms are connected electronically. Firms use new tools to connect business partners and customers (Hackbarth etc, 2000). Furthermore, latest results even show that, to some extent, technology diffusion could be self-propagating rather than driven by exogenous factors (Stoneman, 2007).

The manufacturing sector also includes a number of high-tech industries that have two distinct features (Gao and Pan, 2007). The first is that volatility is relatively greater than in other sectors, in particular where firms collaborate. The other is that high-tech markets are more explicitly differentiated to suit the diversity of consumers' requirements. Although, in contrast to Gao's opinions, Yi (2007) believes the substitution rate in high-tech industry is much greater than in traditional industries. Since knowledge diffuses rapidly in high-tech industry, it is much easier for followers to imitate the latest technology without paying huge R&D costs. This to some extent indicates that it is more difficult to differentiate products in high-tech markets. On the other hand, since knowledge is so important to success in high-tech industry, compared with traditional industries, labour is a less crucial input. Yi therefore claims that the entry barriers in high-tech industry must be lower.

By looking at the Chinese manufacturing sector we will thus be trying to see whether high-tech and IT-based industries differ from more traditional industries and also whether the experience in developing countries differs from that of developed countries. However, as the data size would dramatically decrease if we restricted the high-tech industries based upon the OECD's classification of high-tech industries, we may not able to particularly distinguish the high-tech industries from the manufacturing industries. Instead, in order to explore the unique impacts of innovative decisions in high-tech industries, we examine whether firms located at high-tech zone (Qingshanhu District) innovate (or collaborate) more than firms located at non high-tech zone (the other seven districts at Nan Chang). In particular, in the empirical studies, we would also investigate whether the collaboration cost percentage in high-tech firms located at the high-tech zone is less than firms in other districts.

The second stream that runs throughout the literature discussed above concerns theoretical approaches to modelling collaboration. As is clear there are many. Some are transaction cost based, some are risk sharing based, some are more based on trust and others are based on theories of organisational behaviour. Obviously there is a limit to what can be undertaken in one thesis and thus an initial choice has to be made as to the theoretical or conceptual approach that is to be pursued. The choice that has been made is that the prime approach to be employed is to model using game theoretic approaches.

There is a pedigree of past models in this mould that can be built upon. It has been shown above, however, that many game theoretic innovation models do not even allow for collaboration. The first extension we make to the literature is to allow for collaboration. The second extension we make is that our model, for the first time, explores the development cost sharing plan under collaboration from the viewpoint of the low technology firm. As a result we detail how the cost percentages vary with various market characteristics. The third extension to be made is that, unlike in most existing models which exclusively consider process innovation. We consider product innovation which we argue is much more prevalent. In fact it will be allowed that each firm has a distinct nature and technology level and firms will base their decisions on their expected discounted utility and current profits. A firm may choose either collaboration or competition. If it chooses competition the firm would also have the choice between innovation and imitation through time. The winner of each innovative R&D race discovers how to produce a new superior product, and the winner of each imitation race discovers how to produce the state-of-the-art quality product.

The resulting analysis provides insight into when collaboration might occur (it depends upon transaction costs, market type, various market characteristics, and the possibility of imitation but not simply), how development costs are shared across collaborators (it varies with market characteristics, although the cost paid by the low technology firm will not exceed 100% in a four-strategy set, it may pay more than 100% in a three-strategy set in rare cases), and we are also able to make some predictions about changes in firms' revenue over time as innovation occurs. These predictions are used to guide an analysis of panel data upon technological collaboration in Chinese manufacturing in later chapters.

3 Competition vs. Collaboration: A Game Theory Approach

3.1 Introduction

This Chapter provides a game theoretic exploration of the decisions of firms on whether to compete or collaborate in the generation and adoption of a sequence of new technologies.

The basic assumptions of the theoretic model employed are similar to the patent race model proposed by Vickers (1986), except that here there are three main changes. First, the innovations considered here include product innovations whereas in Vickers (1986) only process innovations are discussed. Secondly, in Vickers (1986) firms always compete in innovation whereas here the model is extended so that firms may compete, collaborate or imitate in the generation and adoption of new technology, with the choice of strategy being endogenous to the model. Thirdly, transaction costs, which are not considered at all by Vickers are considered as one of the factors affecting decisions to collaborate in both three-strategy set and four-strategy set variants.

In the next section, the general modelling concept and assumptions are discussed. A matter of some importance concerns the Intellectual Property Rights (IPR) regime. If this regime is strong then imitation will not be possible. If it is weak then imitation will be possible. In section 3.3 models in which imitation is not possible and therefore where the possible strategies of the firm encompass innovation, collaboration and do nothing, are detailed. In section 3.4 models of strategy in which imitation is possible and where the strategy sets encompass innovation, collaboration, imitation, and do nothing are discussed. In section 3.5, we consider a particular example to illustrate our theory illustrating the Cournot equilibrium for both the three and the four-strategy cases. Brief conclusions and a discussion of limitations are provided in section 3.6.

3.2 The Modelling Concept and Assumptions

3.2.1 General

Since the framework employed was inspired by the Vickers (1986) model with its sequence of innovations, many of the basic assumptions remain as stated by Vickers. Specifically:

a) We consider a duopoly market in which the two firms play two stage games with two non-homogeneous products. In particular, firms decide what quality of goods and which strategy is optimal to adopt in the first stage, and they compete with each other on price in the second stage.

b) Although we have shown in Chapter 2 that collaboration between firms in the development of new technology may be a reaction to market and technological uncertainty, Vickers assumes that in a patent race game firms have complete information and thus there is no uncertainty. Therefore, no matter which strategy firms choose (innovation, imitation, collaboration or do nothing), no risk is involved and the only determinant identifying the best strategy is the payoff to each strategy option. The patent race to innovate can then be regarded as a simple deterministic bidding game (Dasgupta, 1982; Gilbert and Newbery, 1982). Just as Vickers (1986) suggested, for the sake of simplicity, we also assume that firms have complete information and thus uncertainty as an issue is put on one side[1].

c) In Vickers's model, firms compete in a game to acquire a superior technology offered by a third party. He assumes that the acquirer obtains the IPR or patent rights to the technology and thus the game may be considered to be a patent race. The winner of the race will have exclusive rights to the technology at the date of the race. This will allow the winner to become technologically superior to his competitor(s) with no possibility that the new technology may be stolen by his rivals in the period. Other firms may only attain the same performance as the winner when the next round of the sub bidding game finishes. We initially develop models where these assumptions with respect to IPR are maintained. However in later work we relax the assumptions on IPR.

d) In Vickers (1986) the firm's payoff to different strategies mainly depends upon it and its rivals levels of technology, labelled the technology gap. In particular, as Vickers (1986) addresses, the firms' relative technology levels may decide the firms' current profit flows. Since each sub game only finishes when one player successfully bids, the superior technology level must move up one step at a time. This however does not mean that the technology gap between players always remain at one generation. If a player continually wins, for instance for n steps, then the gap between him and his rival would be n plus the initial technology gap at the beginning of the game. In fact there may be two sequences of outcomes: either a market where the market leader always dominates in

[1] Although some researchers suggest that lack of information does not necessarily prevent cooperation/ collaboration to reach Pareto efficiency (Kaitala et al, 1995), the initial assumptions of the game that we designed still follow Vickers' models that only allow complete information.

each sub game – a persistent dominance market; or a market where the follower in sub games always overthrows the previous winner, known as an action-reaction market. Vickers suggests that there are important differences between such markets and we thus also explore such issues, being keen to know what the firms' responses will be in the two different types of market.

In addition to these similarities to the work of Vickers we have also introduced some extensions.

e) The most important extension that we introduce is that we allow firms to collaborate in the development of new technology. Thus whereas in Vickers firms essentially may innovate or do nothing, we initially allow that firms may innovate, collaborate or do nothing (a three-strategy model). We consider this three-strategy framework as appropriate when there are strict IPR regimes as assumed in the original Vickers model.

f) Often, however, IPR is weak and this raises the possibility that firms may imitate rather than innovate (with or without collaboration). Thus in later work we relax the assumptions on IPR and consider the possibility of imitation, which allows followers to copy the superior technology with certain searching cost, so that each firm face four strategies – innovate, collaborate, imitate or do nothing – rather than three.

g) Vickers model is built around process innovation and the nature of superior technology is concerned with cost reduction only. The firm with the most cost efficient technology will dominate the market and consequently obtain monopoly profits. However, if there is product differentiation then a cost advantage does not guarantee monopoly profits. Product differentiation may arise in many ways, such as brand, design, different quality products and embedded customer service. Firms with a superior technology will have greater comparative advantages when they compete, but they may not completely squeeze rivals out of the market. Less productively efficient firms may also survive through product differentiation even though their technology level is not the best. This indicates that only considering process innovation may not be sufficient. We need to also consider product innovation in the game. We thus allow for both product and process innovation, instead of analyzing process innovation alone, by employing an improved consumers' utility function.

h) As Vickers does not allow for collaboration he has no need to consider transaction costs. In the previous chapter we have argued however that the possibility of firms collaborating may well be influenced by whether there are transactions cost and if so how large they might be. Thus in addition to the R&D cost normally addressed in studies of innovation we also allow for transaction cost arising when firms' collaborate, covering the additional cost of coordination, negotiation and safeguards embedded in collaboration. In particular, when firms collaborate, there are various cost sharing possibilities and the costs of negotiation may effectively push the market to reach an equilibrium (please refer to section 3.5).

The models that we proceed to develop thus allow that firms may innovate i.e. develop new technology alone, collaborate in new technology development, imitate (i.e. copy the leaders technology with certain cost) or do nothing. These are the alternative strategies that we model below. There is however another alternative. This alternative is licensing. In essence, if licensing occurs than the winner of the patent race allows his rival to use the new technology that he owns for a royalty fee.

Of course, licensing will only occur in a world where IPR is strong. Otherwise technology may be copied or stolen at lower cost which must be preferable to the acquirer. Thus licensing is only relevant in our three-strategy models. If licensing were to be introduced in such models they would be similar to the four-strategy models, but with a fee being paid by the imitator. Rather than do this however we have decided to rule out licensing strategies. Vickers does not allow for licensing and neither do we. This not only simplifies our analysis but also means that we do not have to incorporate many of the other issues that a consideration of licensing would require. For example, some of the issues that are raised in the literature on licensing are that:

(i) Licensing may severely threaten the dominant position of a technology leader. Some empirical studies also show that in order to better adapt to local tastes, North to South licensing encourages the South to establish local research centres to improve licensed innovations (Larson & Anderson, 1994; Blumenthal, 1976). Such licensee behaviour may potentially threaten the technology owner’s dominant position by increasing the risks of being overtaken by the licensee. If licensing stimulates the technology follower to innovate more locally, the best licensing strategy for the licensor is to grant a contract to the licensee with the least risk-adverse preferences who will accept the offer. But to achieve that goal, the market must be open enough to allow the licensor to observe his rival’s risk preferences. To some extent, this market restriction is too strict in most situations. The problem is, when the potential licensee’s risk preference is unobservable, there is no steady strategic equilibrium for licensor.

(ii) Gallini and Winter (1985) also support the idea that licensing may threaten the licensor's technology dominance. After analysing a case of process innovation, they believe that providing a license would result in more efficient production with less cost - an ex post incentive. Because of such an incentive, the licensee may invest more in self-innovation leaving the licensor with a dilemma (Teece, 1988). That is, granting a license to a rival could yield additional royalty rents but the licensor would have to bear the risk that passing the vital knowledge to his rival would enable that rival to generate a better technology and competitive advantages (Scherer, 1980).

(iii) The licensor has to bear the risk that the licensee will misuse the technology in other areas or in other ways that have not been agreed in the contract (David & Ray, 2006). This risk is inherent in many transactions. If this happens, the licensor has to bear possibilities that the technology buyer expropriates more rents than he should have (called quasi rents by Hill, 1990). To reduce such potential opportunism though cheating, lying or stealing, the licensor may have to invest a large amount in safeguards for surveillance and investigation.

(iv) Finally, as the latest technology may help the inventor to achieve market superiority over his competitors, in order to maximize the monopoly payoff in the post-invention window, the technology inventor normally would not license the technology follower immediately after the discovery of innovation. There may be a time lag, of one year or even more (Baumol, 1992), that will allow the licensor to bring the licensed technology to the market first. In that case, the licensee has to sell the products based on the obsolete technology for a while until the license takes effect. Baumol (1992) reveals a possibility that if the technology owner licenses the innovation to his rivals, the net return on technology will gradually diminish to the cost of capital, indicating the profit of the innovation may fall to zero. Thus, compared to collaboration where both parties own the intellectual property rights at all times, concerns re profit loss may force the licensor not to license their technology or at least, to push the starting date of any license out as far as possible (unless the licensee could recompense the licensor with a large fee).

To repeat, however, we do not consider licensing as a strategy option in our game theoretic model.

3.2.2 The Formal Model

We consider a duopoly market in which the firms play two stage games. At the first stage, firms decide on both the quality of goods to supply and the (technological acquisition) strategy to pursue, whilst at the second stage, firms compete with the rival on price until reaching equilibrium. The two firms are presented over time with a sequence of technological opportunities for a total of T periods and the strategy choice concerns whether to compete, collaborate or imitate in the development and adoption of these technologies.

Figure 3.1 Game Schedule

Innovation sought: $t+k+1$ …… $t+k+n$.

Firms initial technologies: H firm $(t+k)$

L firm $(t+1)$

We assume that in each period there is a superior technology that can be developed that is better than any technologies on offer in the previous k

periods. We order the time periods by the level of the superior technology $t+k+1$ within that time period. As a result, the larger is t the better is the starting point of the technology in that industry. At any point in time the firm with the higher technology level $t+k$ ($k \geq 2$) is defined as H, and the follower using/owning the lower technology level $t+1$, is labelled as L (Figure 3.1). That means the technology gap between two firms must be $k-1$, which is at least one. If only one of the firms acquires the new technology, then its technology level would rise to level $t+k+1$, whist the rivals' level remains the same as previously.

We are particularly interested in whether, given the strategy choices of firms: the market leader (H) will always adopt a new technology and the follower (L) will not, so that there will be persistent dominance (PD) over time; or whether the market follower will always adopt a new technology and a follower will not so there will be action reaction (AR) over time; or whether the firms will collaborate over time with a more balanced outcome. We are especially interested in the conditions that will produce a collaboration outcome and also, with that outcome, the determinants of the collaboration cost that firm L will pay.

Strategic choices will be driven by the relative payoffs to different strategies. Under competition in the generation and adoption of a new technology there are two payoffs to consider. The payoff when the firm has the technology and its rival does not and vice versa. According to the idea of creative destruction, if two firms are competing over the generation and adoption of a new technology one may consider that the one with the largest difference between the two net payoffs will win the technology race.

Both firms are considered to bid in turn until the bid reaches their respective incentives. However, since the decision is made at the beginning of each sub-game, the one with the lower incentive will definitely lose the sub-game and give up bidding automatically. Therefore, the real costs of acquiring a technology via innovation (the difference between gross and net payoffs after payment) are here assumed to equal the R&D costs of the new technology rather than, as in Vickers's auction framework, the maximum amount that the rival would pay. Thus, for each call, no matter who wins the sub-game, the winner always pays the real R&D cost. These incentive comparisons thus addressed here are the trigger by which one my judge which firm wins in pure strategies. Once one firm acquires the latest technology, both firms then move to the next sub-game.

Let $\Omega(s,t)$ denote the net payoff to a firm in the sub-game immediately after a technology auction where s shows the technology level of the firm itself and t indicates the technology level of the rival. For example, in time period $t+k+1$, if the previous leader H wins, indicating a persistent dominance market, then his payoff would be $\Omega(t+k+1,t+1)$, whilst his rival L has payoff $\Omega(t+1,t+k+1)$; if the previous follower L wins, indicating an action reaction market, then the his payoff would be $\Omega(t+k+1,t+k)$, whilst his rival H has payoff $\Omega(t+k,t+k+1)$. Table 3.1 below shows the payoffs in this pure innovation game.

Table 3.1 Firms' Payoff in a Pure Innovation Game

	Win	Lose
H	$\Omega(t+k+1,t+1)$	$\Omega(t+k,t+k+1)$
L	$\Omega(t+k+1,t+k)$	$\Omega(t+1,t+k+1)$

We expect that the net payoff to acquisition is positive. This provides each firm with an incentive to innovate. Thus we have

$$\Omega(t+k+1,t+1) > \Omega(t+k,t+k+1) \qquad (3.1)$$
$$\Omega(t+k+1,t+k) > \Omega(t+1,t+k+1) \qquad (3.2)$$

Following Vickers (1986), we define h_1 (l_1) as the incentives for firms H (L) to win an innovation race. These equal the payoff gap between a winning payoff and non-winning payoff (excluding the costs incurred in pursuing any strategy) as in 3.3 and 3.4 below. Defining letting h_4 (l_4) as the incentive for the firms H (L) to do nothing yields 3.7 and 3.8 below. If either firm imitates then they will both have the same technology levels and both have payoffs of $\Omega(t+k+1,t+k+1)$ so the incentive to imitate, defined as h_3 (l_3), is given by 3.5 and 3.6 below. To distinguish this payoff after imitation from the same payoff from collaboration we use an extra subscript I.

$$h_1 = \Omega(t+k+1,t+1) - \Omega(t+k,t+k+1) \qquad (3.3)$$
$$l_1 = \Omega(t+k+1,t+k) - \Omega(t+1,t+k+1) \qquad (3.4)$$
$$h_3 = \Omega(t+k+1,t+k+1)_I - \Omega(t+k,t+k+1) \qquad (3.5)$$
$$l_3 = \Omega(t+k+1,t+k+1)_I - \Omega(t+1,t+k+1) \qquad (3.6)$$
$$h_4 = \Omega(t+k,t+1) - \Omega(t+k,t+1) = 0 \qquad (3.7)$$
$$l_4 = \Omega(t+1,t+k) - \Omega(t+1,t+k) = 0 \qquad (3.8)$$

If there is competition between firms, then when $h_1 > l_1$ the leader wins and there is a persistent dominance market but if $h_1 < l_1$, then L wins, leading to an action-reaction market. Such ideas based on incentive comparisons are also found in other games e.g. Shaked and Sutton (1984) who analyse a two person non cooperative bargaining game in unemployment.

Firms will either jointly develop new technologies, or jointly acquire new technologies from a third party. We continue to assume however that the firms still compete on the product market. After the game therefore the post-collaboration payoff for the two players should be equal. Define this payoff as $\Omega(t+k+1, t+k+1)_C$, where the capital C denotes collaboration in contrast to imitation which has the same gross payoff.

The incentive to collaborate depends upon the payoff relative to that expected under competition. To simplify matters we assume that both firms assume that under competition they would lose the game, in which case the incentives to collaborate for firms H and L are given by (3.9) and (3.10)

$$h_2 = \Omega(t+k+1, t+k+1)_C - \Omega(t+k, t+k+1) \tag{3.9}$$
$$l_2 = \Omega(t+k+1, t+k+1)_C - \Omega(t+1, t+k+1) \tag{3.10}$$

We assume, in addition, that $h_i > 0$ & $l_i > 0$ $i = 1,2,3$ reflecting that the best strategy for any firm with a negative incentive is to 'do nothing'. This rule indicates that the bidding price from an individual firm must not be bigger than his innovative incentive no matter what decision that firm makes. It makes sense that they should earn non-negative profits from the deal. The player who loses the game under competition is also considered to 'do nothing'.

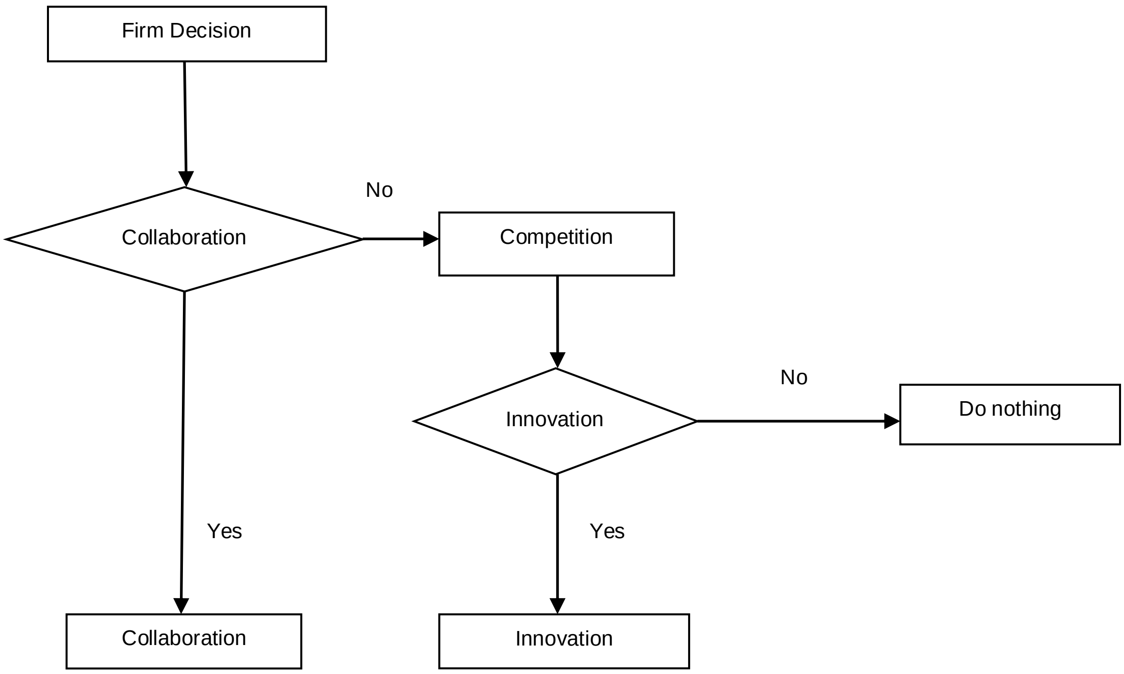
3.3 The Three-Strategy Set (Innovation, Collaboration, or Do Nothing)

In order to analyse this formal model we initially consider a world where IPR is considerably strong and imitation is not a feasible strategy for either firm. No imitation allowed may be partly because the existence of competitors is quite limited; and also may be the law grants exclusive right to firms which are prerogative in some particular industries. This three-strategy assumption actually provides a simpler model where firms have only three possible strategies: innovation, collaboration and do nothing. This differs from the Vickers model in allowing collaboration.

Under what conditions will the two firms choose to collaborate rather than compete? This will of course depend upon the net payoffs to the two strategies, with collaboration requiring that **both firms** are better off than otherwise. To compare the incentives of different strategies, we propose a number of comparison paths for both firms. The flow chart (Figure 3.2) illustrates the incentive comparison in most conventional competition games.

The flow chart is designed by using computer programming rules. Rectangles represent determined processes, whilst diamonds represent undetermined decisions. Arrows show the incentive comparison paths from one process to another. If the firm accepts the undetermined decision in the diamond, then the strategy he chooses follows the ‘Yes’ path. Otherwise, the arrow showing process picks ‘No’ path.

Figure 3.2 Decision Flow Chart: Three-Strategy Set



For instance, when a firm encounters an opportunity to launch a new technology, he must firstly decide if he ought to collaborate. If he does not collaborate, then he moves to the process of competition. He then needs to determine whether he will innovate. If yes, then his strategy would be innovation. Otherwise, 'do nothing' seems his only other option. In fact, this flow chart emphasises how a firm will choose its strategy rather than having its strategy predetermined (an idea also reflected in figure 2.1 in chapter 2).

Table 3.2 is provided as a means by which the game process can be better understood. There are various possible combinations of gross payoffs, but according to flow chart 3.2, it is clear how to work out the strategy equilibrium in each case by comparing different incentives.

Table 3.2 Decision Table under Three-Strategy Set

Market Type	Available Strategy	Initial Outcome	Final Outcome	Explanation
$h_1 > l_1$ (PD)	H: h_1, h_2 L: l_2, l_4	(h_1, l_2)	(h_1, l_4)	H: Innovation L: Do nothing
		(h_1, l_4)	(h_1, l_4)	H: Innovation L: Do nothing
		(h_2, l_2)	(h_2, l_2)	**Collaboration**
		(h_2, l_4)	(h_1, l_4)	H: Innovation L: Do nothing
$h_1 < l_1$ (AR)	H: h_2, h_4 L: l_1, l_2	(h_2, l_1)	(h_4, l_1)	H: Do nothing L: Innovation
		(h_2, l_2)	(h_2, l_2)	**Collaboration**
		(h_4, l_1)	(h_4, l_1)	H: Do nothing L: Innovation
		(h_4, l_2)	(h_4, l_1)	H: Do nothing L: Innovation

The first column in the decision Table 3.2 shows market type (persistent dominance or action reaction) according to whether the leader or follower has the larger payoff in a competition game without a collaboration option. This indicates whether the leader or follower would win that game. The loser of the game also has the option of doing nothing. The second column represents the making of the first decision by comparing the incentives to collaboration and competition (which in fact, is denoted by the incentive to innovate if the firm wins under competition, or the incentive to do nothing if the firm loses). Therefore, the decision in the first diamond of flow chart 3.2 depends upon which strategy, collaboration or competition, has the bigger incentive. The third column shows the firms' initial choices after the incentive comparison. However, as the collaboration equilibrium will be attained only when both players agree to collaborate, the situation that one firm prefers to collaborate and one does not must lead to competition, giving us the final outcomes in column four and the corresponding explanations in column five, respectively. Since the strategy equilibrium in this decision table appears symmetric upon each market type, to avoid tedium, we only read the table in the case of a persistent dominance market. The argument for the action reaction market is then obvious.

With a persistent dominance market $h_1 > l_1$, thus the firm with the higher technology level, H, must win any competitive race. This means that the laggard, L, would not choose innovation and must pursue the next available option i.e. do nothing. Therefore, in a persistent dominance market, for firm L, the innovation option is actually redundant. Thus, as listed in column two, the potential strategies for H are collaboration and innovation, whilst the potential strategies for firm L are collaboration and do nothing. According to flow chart 3.2, to make an optimal choice, the firms compare the payoffs to each strategy and maximize their possible incentives. There are two possible strategies that might be chosen by each player. Thus, the combination of gross payoffs must be $C_2^1 \times C_2^1 = 4$, as listed in column three. The first of the possible initial outcomes in a persistent dominance market, (h_1, l_2), for instance, shows the highest strategic incentive for firm H is h_1, indicating $h_1 \geq h_2$, whilst the best strategy for firm L is l_2, because $l_2 \geq l_1$. This indicates that H prefers innovation and L prefers collaboration. However, as there is no way to supply H with a higher payoff through collaboration, H would definitely not accept a collaboration offer made by L. Thus, the game becomes a pure competition game, although L's incentive to play this game is less than his incentive to collaborate. Firm L thus chooses the alternative strategy, do nothing, and the final outcome is (h_1, l_4). Looking at the second combination of possible initial outcomes in a persistent dominance market, we notice that the final outcome is that H innovates and L chooses do nothing. But the difference is that compared to the first example, L genuinely prefers this combination, whilst previously L preferred collaboration which was not available. The third possible initial outcome is, (h_2, l_2), with both firms wanting to collaborate. This initial outcome will then become final. However it should be noted that for both firms to want to collaborate it is necessary that $h_2 \geq h_1$ and $l_2 \geq l_4$. The fourth possible initial outcome, using similar arguments yields an (h_1, l_4) final outcome.

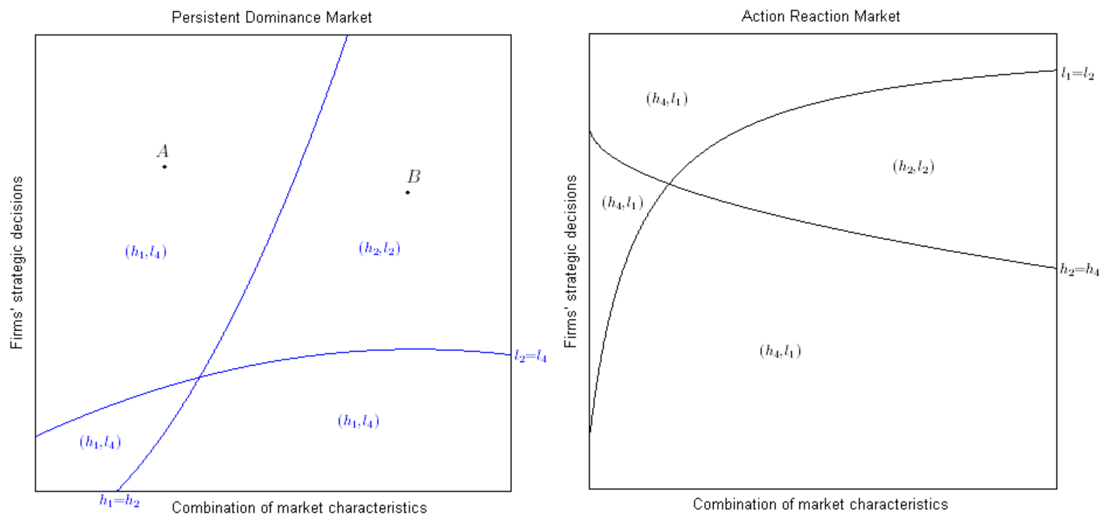
Extending the analysis to the action reaction market, we derive that collaboration will occur in two different situations (Table 3.3), one when the market is of persistent dominance type, the other where it is of the action reaction type.

Table 3.3 Collaboration Conditions in Three-Strategy Set

Situation	Market Type	Collaborate Incentive Restrictions
I	$h_1 > l_1$;	$h_2 \geq h_1$; $l_2 \geq l_4$
II	$h_1 < l_1$;	$l_2 \geq l_1$; $h_2 \geq h_4$

To better understand how the decision table (Table 3.2) and the collaboration condition table (Table 3.3) work, we demonstrate these ideas with a simple example. The decision map (Figure 3.3) shows how firms choose their optimal strategies upon different markets. The horizontal axes of these decision maps illustrate a combination of various market characteristics, including market concentration, degree of product substitution, market size, discount rate of price sensitiveness etc., whilst the vertical axes reveals firms' incentives under different strategies, indicating various market response sets which depend upon each player's optimal strategy (with the highest possible incentive).

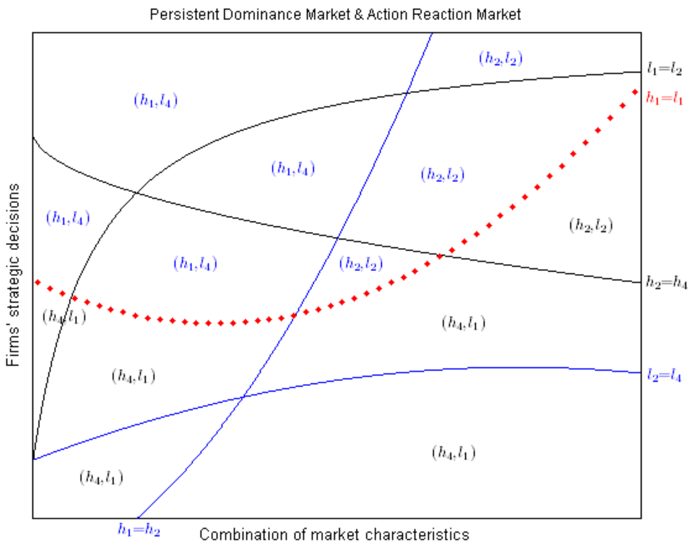
Figure 3.3 Decision Map of Three-Strategy Set upon Market Types



In particular, the decision map for each market type, distinguishes four areas. In the first the space is split according to whether $h_2 \geq h_1$; and $l_2 \geq l_4$ whereas in the second, space is split according to whether $h_2 > h_4$ and $l_1 > l_2$ these curves representing the two incentive comparisons. In particular, above curves, firms prefer the incentive with the smaller corner mark. For instance, point B in the persistent dominance market is above the curve $l_2 - l_4 = 0$, showing the incentive for firm L here must be $l_2 > l_4$, which consequently tells us firm L prefers l_2 more than l_4.Thus the optimal strategy for firm L in this area is l_2 (collaboration) and the market equilibrium for this point is (h_2, l_2) (collaboration , collaboration). In contrast, as point A is above $l_2 = l_4$ and $h_1 = h_2$, at point A firm H prefers h_1, whilst L desires l_2. Therefore, the expected best strategy in this case might be (h_1, l_2) (innovation, collaboration). But as explained in Table 3.2 as (h_1, l_2) is not reachable unless both parties agree to collaborate, the market finally generates the outcome (h_1, l_4) by downgrading L firm's incentive from the best strategy l_2 to second best strategy l_4. The firms' decision equilibrium is shown for each space with each point representing a status that encompasses both players' strategic decisions.

To show how firms strategic decisions might move (even alter) as market type changes we integrate the two boxes. Figure 3.4 generates a combined decision map by introducing a red U shape like market type curve ($h_1 = l_1$). For convenience, we also mark all restrictions and strategy equilibria in blue and black upon the two different markets, respectively.

Figure 3.4 Combined Decision Map of Three-Strategy Set



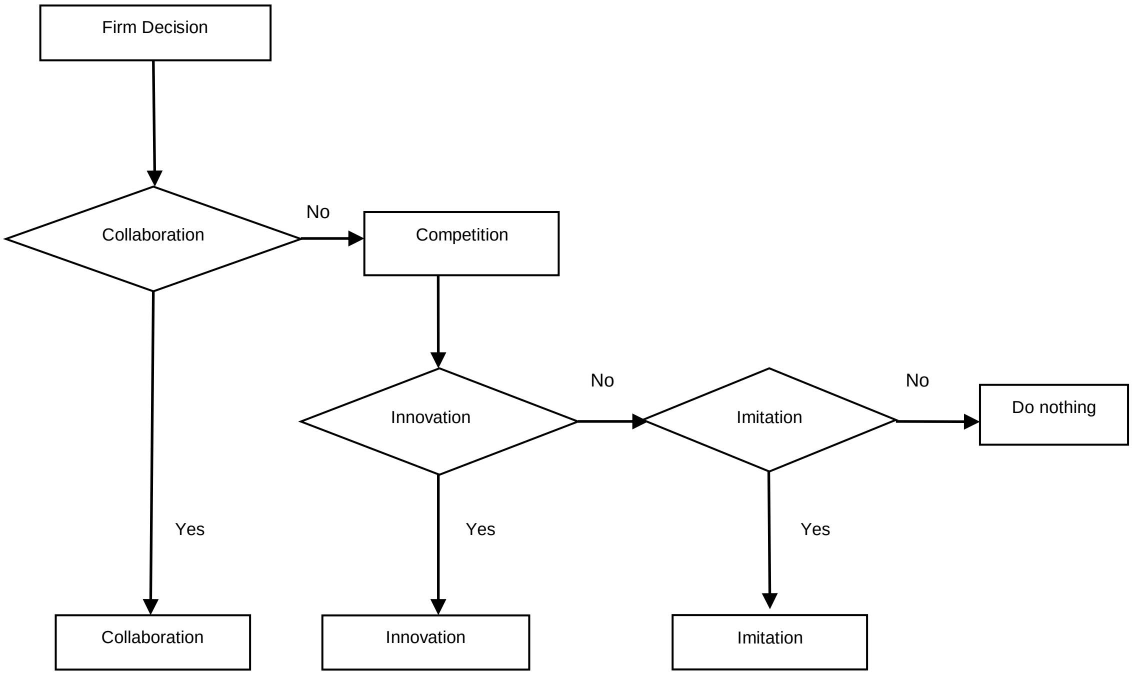
Points above $h_1 = l_1$ are such that $h_1 > l_1$, indicating a persistent dominance market. Therefore above the red curve the decision allocation rules must follow those of a persistent dominance market, whilst all points below $h_1 = l_1$ comply with strategy combinations in an action reaction market.

Although the shape of the curves assumed in Figures 3.2 and 3.3 may change with market characteristics and the definition of the strategy incentive functions, this approach offers a unique angle from which to observe the decision table generated from the framework and provides some insight in to how firms' decisions change when incentive restriction or market type change.

The figure also provides other benefits: firstly, it shows there is no room for other strategy combinations and the possibilities we addressed in table 3.2 fill the decision map for the three-strategy case. Secondly, it helps us to understand the boundaries of each final combination, for instance, if we simply shift the curve $h_1 = h_2$ to a higher level or squeeze the curve $l_2 = l_4$ to a lower position then there will be more opportunities for collaboration in the persistent dominance market. Thirdly, it will also allow us to consider extra strategies over and above the three considered here. It is to that which we now turn.

3.4 The Four-Strategy Set (Innovation, Collaboration, Imitation, Do Nothing)

Figure 3.5 Decision Flow Chart: Four-Strategy Set



Innovation and do nothing are sometimes not the only strategies available to firms in a technology competition. If IPR is not too strict, it may be the case that a firm may be able to imitate its rivals and acquire new technology in that way. Of course imitation may still involve some costs such as search and learning cost but normally such costs would be expected to be less than the self-innovation cost. To introduce the possibility of imitation we create a new decision flow chart in Figure 3.5.

By following the logic in section 3.3, the old flow chart (Figure 3.2) is expanded by adding an imitation option. In Figure 3.5, firms can now choose to imitate if they fail in an innovation auction. Thus, as assumed in three-strategy case, if a firm wins under competition, the possible strategy incentives he compares encompass either collaboration or innovation. But if a firm fails in the innovation auction, now his possible strategy set contains collaboration, do nothing and imitation. A new decision table is thus generated as in Table 3.4, showing six initial outcome combinations for each market type ($C_2^1 \times C_3^1 = 6$). Firms then choose the initial outcome combination with the highest incentive as their optimal strategy.

Table 3.4 Decision Table under the Four-Strategy Set

Market Type	Available Strategy	Initial Outcome	Final Outcome	Explanation
$h_1 > l_1$ (PD)	H: h_1, h_2 L: l_2, l_3, l_4	(h_1, l_2)	(h_1, l_3)	H: Innovation L: Imitation
			(h_1, l_4)	H: Innovation L: Do nothing
		(h_1, l_3)	(h_1, l_3)	H: Innovation L: Imitation
		(h_1, l_4)	(h_1, l_4)	H: Innovation L: Do nothing
		(h_2, l_2)	(h_2, l_2)	**Collaboration**
		(h_2, l_3)	(h_1, l_3)	H: Innovation L: Imitation
		(h_2, l_4)	(h_1, l_4)	H: Innovation L: Do nothing
$h_1 < l_1$ (AR)	H: h_2, h_3, h_4 L: l_1, l_2	(h_2, l_1)	(h_3, l_1)	H: Imitation L: Innovation
			(h_4, l_1)	H: Do nothing L: Innovation
		(h_3, l_1)	(h_3, l_1)	H: Imitation L: Innovation
		(h_4, l_1)	(h_4, l_1)	H: Do nothing L: Innovation
		(h_2, l_2)	(h_2, l_2)	**Collaboration**
		(h_3, l_2)	(h_3, l_1)	H: Imitation L: Innovation

	(h_4, l_2)	(h_4, l_1)	H: Do nothing L: Innovation

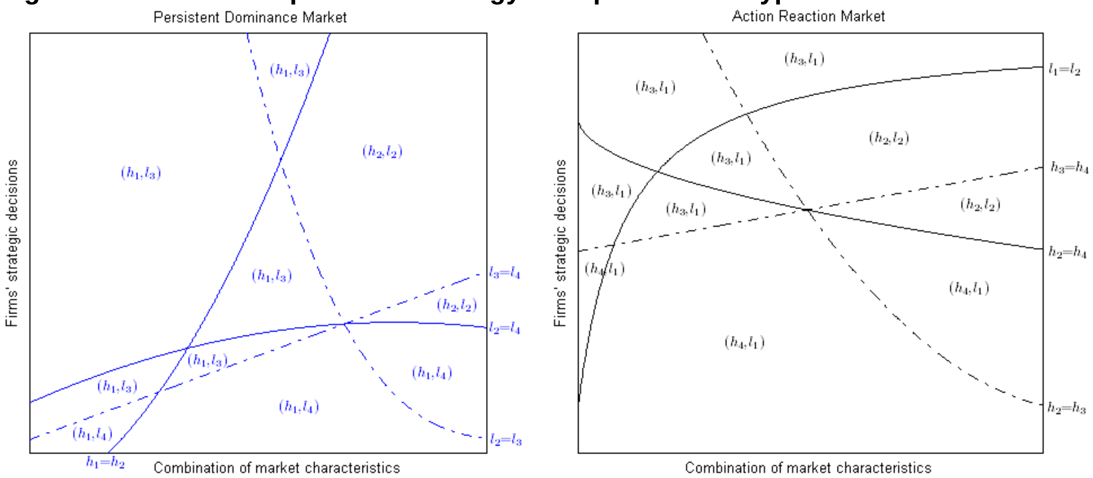
In a persistent dominance market, for example, if $h_1 \geq h_2$, $l_2 \geq l_3$ and $l_2 \geq l_4$, firm H must prefer h_1 (innovation), whilst L likes l_2 (collaboration), resulting in the initial outcome (h_1, l_2). However, as collaboration does not offer a higher incentive for H ($h_2 < h_1$), the firm with the higher technology level will refuse to collaborate with L. Thus, L has to compete with H by choosing the higher payoff from imitation and do nothing. So the final outcome in this combination turns out to be (h_1, l_3) when $l_3 \geq l_4$; and (h_1, l_4) when $l_3 < l_4$. Similarly, by employing this method, other final outcomes in the decision table may also be decided. We then extract from table 3.4 when collaboration may occur in the two different market types to form collaboration condition table in a four-strategy set (Table 3.5).

Table 3.5 Collaboration Conditions in a Four-Strategy Set

Situation	Market Type	Collaborate Incentive Restrictions
I	$h_1 > l_1$;	$h_2 \geq h_1$; $l_2 \geq l_4$; $l_2 \geq l_3$
II	$h_1 < l_1$;	$l_2 \geq l_1$; $h_2 \geq h_4$; $h_2 \geq h_3$

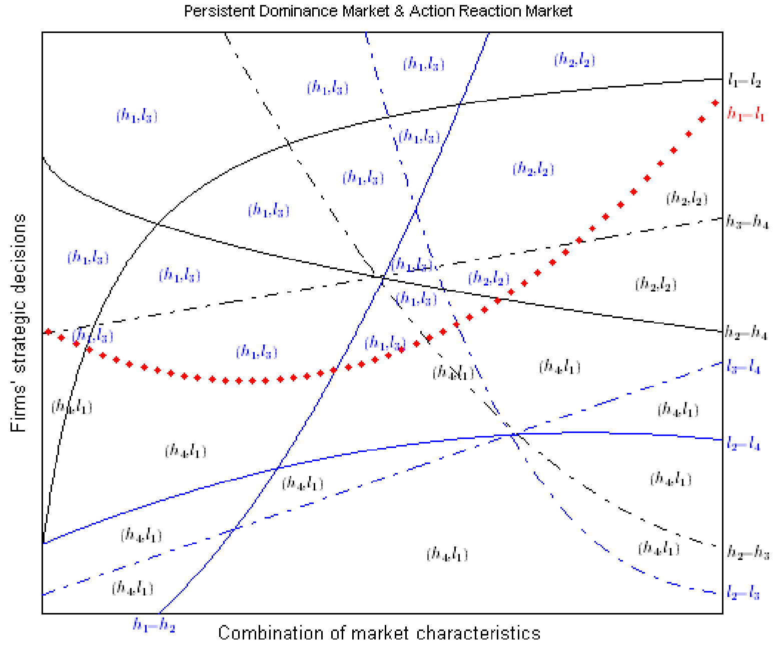
Similar to above, we may demonstrate how imitation affects the firms' decision map by adding two extra incentive restrictions into Figure 3.3, marked by dashed lines in Figure 3.6. Each final outcome in Table 3.4 has been allocated to a corresponding area in the decision map. Comparing with Figure 3.3, we notice that taking account of imitation imposes extra restrictions onto the strategy set and decreases the collaboration area (h_2, l_2) in both market types. Essentially this is because the firm may prefer to imitate rather than collaborate. In the persistent dominance market, for instance, points in the triangle in the middle of the box originally belonged to collaboration in the three-strategy case. But since for points below the curve $l_2 = l_3$ firm L here prefers imitation, this will replace collaboration. The final outcome therefore, turns to be H innovates and L imitates rather than both collaborate.

Figure 3.6 Decision Map of Four-Strategy Set upon Market Types



Again, to better observe the whole decision map in a dynamic market, we integrated the two decision maps of different market types (Figure 3.7). We retain the market type curve ($h_1 = l_1$) as in three-strategy case. As shown in the following figure, all the area above the red curve may be regarded as a persistent dominance market, occupied by blue decision outcomes whilst all the area below the market type curve is an action reaction market, highlighted by black outcomes. Since imitation diminishes the area of collaboration in both market types, it definitely decreases the combinations producing collaboration (h_2, l_2) in the general decision map. Although we should note that the standard to identity market type ($h_1 = h_2$) might vary with actual cases, the ideas embodies in this box still greatly help us to better understand the distribution of decision equilibria (Table 3.4).

Figure 3.7 Combined Decision Map of Four-Strategy Set



3.5 An Example

For illustrative purposes we now construct an example two stage model of the above kind. We suppose there are two firms that compete in a product market each with one product. Using backward induction, we firstly analyse a Cournot equilibrium in prices at the second stage and then look at strategic choices at the first stage as regards competition, collaboration, imitation etc and thus product qualities.

3.5.1 Utility Function

In contrast to horizontal product differentiation, the concept of vertical product differentiation was introduced earlier by Hotelling (1929) and assumes that distinct products on the market differ according to their quality levels, such goods otherwise being homogeneous. Consumers would then choose (at equal prices) the product offering higher quality. However Shaked and Sutton (1982) argue that there may be a trade-off between a goods' quality and its price. If so, consumers will prefer those goods that offer the best value for money. Following Motta (1991), we allow similar behaviour.

On the other hand, products may be horizontally differentiated which arises when there is no agreed quality ordering over the products on the market e.g. if products differ in terms of colours, designs, and brands. People may thus have completely different product choices although all goods may embody the same technologies.

Shaked and Sutton (1990) use a simple linear model to illustrate that, at equilibrium, there is a relationship between market size and market concentration with a competition effect and an expansion effect depending on the elasticity of substitution. They argue, by considering sequential entry, that pre-emption is not particularly advantageous relative to simultaneous entry. Therefore, in our model, we suppose neither firm has any first mover priority. In each stage of the game, both firms make their decisions simultaneously.

Although it is possible to model innovation as changes in either pure vertical product differentiation or pure horizontal differentiation there would seem some advantages in encompassing both. To some extent, e.g. in the IT industry, much modern innovation concerns not only technology upgrading, but also cost saving, (i.e. changes that are both vertical product differentiation and horizontal product differentiation). Shaked and Sutton (1990), propose a utility function that incorporates both horizontal and vertical product differentiation. Earlier Shaked and Sutton (1987) has also integrated both horizontal and vertical differentiation to explore the determinants of market size and market concentration. They found that with product improvements, market size is particularly affected not by the size of fixed cost but by the ability to substitute from fixed cost (R&D) to variable cost. However, as they realised, their non-cooperative games may have collusion as a preferred outcome and thus such games may also suggest that firms would prefer to collaborate rather than compete. Such models may have some implications for our main concerns here.

We proceed by assuming that consumers maximise utility subject to a budget constraint and following Shaked and Sutton (1987, 1990) and Matsubayashi (2007) we write the utility function in an indirect utility form: (3.11)

$$U = -\beta[u_i x_i]^2 - \beta[u_j x_j]^2 - \beta\sigma(u_i x_i)(u_j x_j) + \alpha(u_i x_i) + \alpha(u_j x_j) + M \tag{3.11}$$

Where $M = Y - w_i x_i - w_j x_j$

$$w_i = p_i - \gamma(u_i - u_j) \tag{3.12}$$

This utility function is composed of two parts, utility from (constrained) income M and utility from each player consuming two goods. Matsubayashi (2007) claims that consumer's utility, in fact, is related to the perceived price, but not the real price they pay. That is to say, for instance, the utility to consumers given by two products with same price but different technologies must differ. Even though their prices may be identical, the product embodying higher technology must generate greater utility. Goods with higher technology potentially decrease the perceived price, which gives consumers more utility. However, Matsubayashi ignores the cross competitor effects of product technology. When i's rival, j upgrades his product technology level, it must increase the consumers' perceived price for i goods, although neither i's real price, nor technology level changes. Therefore, we assume that perceived price, w_i for goods i is influenced by both own technology level and the technology gap between himself and his competitor. u_i and u_j are the per unit utilities generated by the two goods i and j with distinct technology levels. In particular, the higher is the technology level of the product, the higher is the utility the consumer may gain from each good. Note that as each firm only produces one kind of good in the market, either player could offer either u_i or u_j . Positive parameters α , γ and β reflect market characteristic. In particular, β reflects the symmetry degree of the market and when β = 1, it indicates a symmetric market with both firms of the same size. γ is the discount rate of price sensitiveness to the products technology changes. It decreases the perceived price when technology gap grows between the firm himself and his rival.

Similar to Shaked and Sutton, (1990), we introduce a parameter σ ($\sigma \in [0,2)$) as an index of substitution to represent not only consumers' unique preferences, but also to explore the degree of market concentration. In particular, when $\sigma = 0$, there is no substitution effect, even if the products have identical technologies. With pure vertical product differentiation $\sigma = 0$ and (3.13) holds

$$U = -\beta[u_i x_i]^2 - \beta[u_j x_j]^2 + \alpha(u_i x_i) + \alpha(u_j x_j) + M \; ; \qquad (3.13)$$

On the other hand, if firms' technology level remains the same, the model turns into a pure horizon product differentiation model. In this case, as $u_i = u_j$ (3.14) holds

$$U = -\beta[u_i x_i]^2 - \beta[u_i x_j]^2 - \beta\sigma(u_i x_i)(u_i x_j) + \alpha(u_i x_i) + \alpha(u_i x_j) + Y - p_i x_i - p_j x_j \quad (3.14)$$

In addition setting $u_i = u_j$ enables representation of process innovation. In fact, process innovation is pure horizontal product innovation and decreasing unit variable cost (in rare cases, it could be increasing (Matsubayashi, 2007)). Therefore, the utility function is ideal for considering both process innovation and product innovation.

3.5.2 Cost Function

The firms' cost function consists of fixed cost (R&D) and variable costs and is assumed to be capable of being written as (3.15)

$$(1-\phi)u_i\lambda^2 + \Lambda\theta(x_i + x_j), \quad (3.15)$$

where $\phi = \dfrac{\Psi * \mu}{|u_i - u_j|}$; $0 < \mu < 1$ (3.16)

The first term of (3.15) denotes the real R&D spending on developing new technology. Spillover effects containing μ, u_i, u_j and Ψ, are denoted by ϕ, to measure the ease of imitation (Motta, 1991). It is assumed that ϕ declines as the technology gap with the other product (k – 1) increases and the greater is the technology gap between players, the more difficult it is for the follower to steal technology from the leader. If $k \geq 2$ and $0 < \mu < 1$, it is easy to show that the minimum gap in product technologies is 1, which ensures that $\phi \in [0,1]$. In addition, following Matsubayashi's, (2007) assumption, we suppose a linear increasing relationship between product quality and R&D, whose unit cost is measured by λ^2.

The second term of the RHS of (3.15) is the transaction cost involved in collaboration encompassing the unit transaction cost θ and the joint output level $(x_i + x_j)$. As stated in section 2.3.4, some scholars believe that the IPR works on collaboration indirectly through transaction cost (Schroder, 2005; Cassiman & Veugelers, 2006), thus, instead of incorporating it in R&D cost, we introduce this term as an extra cost that firms incur when they collaborate. In particular, as incurring transaction cost will help guarantee realisation of the post collaboration payoff by diminishing opportunism, it will assist in helping firms come to an agreement on the sharing of other (e.g. development) costs under collaboration. This may assist in establishing a cost sharing equilibrium. We assume that total transaction costs vary with the size of joint output. The greater is the volume of joint output level, the more difficult will it be for firms to reduce opportunism. This idea is also supported by Dow (1985) who advocates that the unit of transaction cost may vary with capital values and Chen etc (2006), who suggest that transaction cost efficiency moves with output.

We define Λ , Ψ as dummy variables, with a value of either 1 or 0. In particular, Λ is equal to one when firms collaborate, whilst Ψ is equals to one when firms imitate. Thus, depending upon the value of Λ , Ψ , under product innovation, if $\Psi = 0$ (no spillover effect exists), $\Lambda = 0$ (no collaboration), the cost function for innovation turns into

$$C = u_i \lambda^2 ; \qquad (3.17)$$

If $\Psi = 1$ (spillover index $\phi = \dfrac{\Psi * \mu}{|u_i - u_j|}$), $\Lambda = 0$ (no collaboration), the cost function for imitation is

$$C^{I} = (1 - \frac{\mu}{|u_i - u_j|})u_i\lambda^2 \quad , \tag{3.18}$$

If $\Psi = 0$, $\Lambda = 1$, the total cost function for both collaborative firms becomes to

$$C^{C} = u_i\lambda^2 + \theta(x_i + x_j) \tag{3.19}$$

In a collaboration game both firms, rather than just the winner (as under competition), will contribute to R&D costs (or contribute to any bids to acquire technology) and bear transaction costs, they thus share the total cost of R&D, patent fees, expenditure for reducing opportunism etc.). Although both firms will obtain the same technology, this does not mean that they necessarily have to share costs equally. How much each pays depends upon the bargain between the players (Buckley and Casson, 1996). According to our above assumptions on technology cost, one might expect however that the total R&D spending is the same under collaboration as under competition. Also, this condition guarantees that the technology owner will not obtain extra abnormal profit from collaborative behaviour.

Thus, if the target is a product offering utility u_i, we assume that the R&D cost of development is given by (3.17), i.e. $C = u_i\lambda^2$. If let w and v respectively represents the cost paid by firm H and L under collaboration, then by introducing a parameter n, we define the cost portions paid by H and L may be represented by $w = (1-n)C^C$, and $v = nC^C$, which indicates that

$$v + w = nC^C + (1-n)C^C = C^C \tag{3.20}$$

In this model, it is theoretically possible to show that n has a positive value. However in some specific circumstance, n may be negative (Rosenkranz, 1995) if the post-collaboration payoff is so attractive that the leader pays an extra cost to the follower to convince him to agree to collaborate. In that case, the follower may free ride on the launching of the new technology, by accepting a side payment from his rival. In other words, the leader may pay more for the same level of technology achieved under competition. The bargains from collaboration would make it worthwhile.

3.5.3 Cournot Equilibrium

Assume firms i and j are symmetric and denote p^*, x^* as equilibrium price and output respectively. If consumers maximize their utility function, we therefore have the inverse demand equation (3.21)

$$x_i^* = \frac{2u_j(\alpha u_i - w_i) + u_i\sigma(w_j - \alpha u_j)}{u_i^2 u_j \beta(4-\sigma^2)} \tag{3.21}$$

where $$\frac{\partial^2 U}{\partial x_i^2} = -2\beta u_i^2 < 0 \tag{3.22}$$

For each strategic choice we maximize each player's profits subject to the product innovation cost function yielding the equilibrium of price, output, and revenue as follows:

$$p_i^* = \frac{Eu_i}{16-\sigma^2}\ ; \tag{3.23}$$

$$x_i^* = \frac{2E}{\beta(4-\sigma^2)(16-\sigma^2)u_i} \tag{3.24}$$

$$R_i^* = \frac{2E^2}{\beta(4-\sigma^2)(16-\sigma^2)^2} \tag{3.25}$$

$$E = E_1 \text{ OR } E_2$$

where

$$E = E_1 = (\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma u_i}{u_j} - \frac{\gamma(8-\sigma^2)u_j}{u_i},$$

$$E = E_2 = (\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma u_i}{u_j} - \frac{\gamma(8-\sigma^2)u_j}{u_i} + \frac{8\theta}{u_i} + \frac{2\theta\sigma}{u_j}$$

E_1 and E_2 are competition and collaboration strategies respectively. Note, that even though the format of the price equation looks identical for both products, the actual value varies with the technology levels u_i and u_j. As $E_1 < E_2$, to guarantee a positive value for price, product outputs and firms' revenue, we therefore assume the market structure coefficient satisfies

$$\alpha > \alpha_1 = [(\frac{\gamma(8-\sigma^2)u_j}{u_i} - \frac{2\sigma\gamma u_i}{u_j})/(8-\sigma^2-2\sigma)] - \gamma \tag{3.26}$$

We substitute the players' technology level $(t+1)$, and $(t+k)$ into the expression for equilibrium revenue under different situations, then we have

$$R_1 = R_{t+k+1,t+k}{}^* = F\left[(\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma(t+k+1)}{t+k} - \frac{\gamma(8-\sigma^2)(t+k)}{t+k+1}\right]^2 \tag{3.27}$$

$$R_2 = R_{t+k,t+k+1}{}^* = F\left[(\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma(t+k)}{t+k+1} - \frac{\gamma(8-\sigma^2)(t+k+1)}{t+k}\right]^2 \tag{3.28}$$

$$R_3 = R_{t+1,t+k+1}{}^* = F\left[(\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma(t+1)}{t+k+1} - \frac{\gamma(8-\sigma^2)(t+k+1)}{t+1}\right]^2 \tag{3.29}$$

$$R_4 = R_{t+k+1,t+1}{}^* = F\left[(\alpha+\gamma)(8-\sigma^2-2\sigma) + \frac{2\sigma\gamma(t+k+1)}{t+1} - \frac{\gamma(8-\sigma^2)(t+1)}{t+k+1}\right]^2 \tag{3.30}$$

$$R_5 = R_{t+k+1,t+k+1}{}^{I*} = F\alpha^2(8-\sigma^2-2\sigma)^2 \tag{3.31}$$

$$R_6 = R_{t+k+1,t+k+1}{}^{C*} = F[\alpha(8-\sigma^2-2\sigma)+G]^2 \tag{3.32}$$

where $F = \frac{2}{\beta(4-\sigma^2)(16-\sigma^2)^2}$ and $G = \frac{8\theta+2\theta\sigma}{t+k+1}$

Therefore, according to our definitions above of the innovation incentives, the firms' incentives to adopt new technology under different circumstances are as below:

$$l_1 = R_1 - R_3 - C \tag{3.33}$$

$$h_1 = R_4 - R_2 - C \tag{3.34}$$

$$l_2 = R_6 - R_3 - nC^C \tag{3.35}$$

$$h_2 = R_6 - R_2 - (1-n)C^C \tag{3.36}$$

$$l_3 = R_5 - R_3 - C^I \tag{3.37}$$

$$h_3 = R_5 - R_2 - C^I \tag{3.38}$$

$$h_4 = 0 \tag{3.39}$$

$$l_4 = 0 \tag{3.40}$$

It is clear that both R_5 (revenue with imitate) and R_6 (revenue with collaboration) indicate revenues when both firms produce products based on the same technology level. But the value of R_6 is bigger than R_5, showing that firms' revenue must be greater when choosing collaboration instead of imitation. That is because transaction cost diminishes market uncertainties. In other words, we claim that transaction costs help to increase firms' revenue under collaboration. This reflects the fact that collaboration could maximize players' gross payoff. On the other hand, increasing transaction cost will certainly partially absorb profits earned from collaboration. Thus, the net payoff to collaboration actually reflects the trade-off between the cost minimization and rent maximization.

Another observation is that, from the equilibrium functions of price, output and revenue, (3.23)--(3.25), price and revenue are always positively related to u_i, α, and negatively related to u_j, β, whilst output is only positively related to α, and negatively related to u_j, β. Thus,

Prediction 1: Increases in the rival's product technology level and market size or decreases in the market structure coefficient, will decrease the firm's price, output and revenue.

Prediction 2: Increasing the firm's own technology level must increase its price level and revenue (which reflects the theory of creative destruction).

In the following section, we will look into firms' various incentives in different situations to explore under what circumstance firms prefer collaboration and in particular, what the cost sharing plan will be if players choose to collaborate. We first analyse the three-strategy case with collaboration, innovation and do nothing, with both persistent dominance market and action reaction markets separately explored. In section 3.5.5, further investigation adds imitation as an extra restriction. This analysis leads to further modelling predictions.

3.5.4 The Three-Strategy Set

We first investigate the determinants of whether firms collaborate and how the costs are shared in a collaboration fort the three-strategy case. We consider the persistent dominance and the action reaction markets separately.

Persistent dominance market

According to situation I in table 3.3, collaboration will occur in a persistent dominance market if:

1. $h_1 > l_1$
2. $h_2 \geq h_1$
3. $l_2 \geq l_4$

Of which the first requirement $h_1 > l_1$, indicates that the market type is persistent dominance. Substituting (3.27) to (3.30), into h_1, l_1, we then get the constraint

$h_1 - l_1$=(3.30)-(3.28)-(3.27)+(3.29)>0

which is equivalent to

$$\alpha \leq \alpha_3 = \frac{\gamma\left[4\sigma^2 + (8-\sigma^2)^2\right]\left[(t+k+1)^2(t+k) + (t+1)^2(t+k) + (t+1)\right]}{2(8-\sigma^2-2\sigma)^2(t+1)(t+k)(t+k+1)} + \frac{4\gamma\sigma(8-\sigma^2)}{(8-\sigma^2-2\sigma)^2} \quad (3.41)$$

Similarly, for requirement 2 & 3, $h_2 \geq h_1$ & $l_2 \geq l_4$, we require that

$$n \geq n_1 = \frac{\theta(x_i + x_j) + R_4 - R_6}{C + \theta(x_i + x_j)} \quad (3.42)$$

$$n \leq n_2 = \frac{R_6 - R_3}{C + \theta(x_i + x_j)} \quad (3.43)$$

(3.42) and (3.43) jointly suggest that if (3.41) is met then the firms may collaborate if n is in the range of $n \in [n_1, n_2]$. Obviously to avoid n's upper bound n_1 being smaller than its lower bound n_2, α must be limited in the range of

$$\alpha \geq \alpha_2 = \frac{M_1^2 + N_1^2 + \frac{\theta G}{t+k+1} - 2G^2}{(8-\sigma^2-2\sigma)\left[2(2G + N_1 - M_1) - \frac{\theta}{t+k+1}\right]}. \quad (3.44)$$

where $M_1 = \gamma k(\frac{8-\sigma^2}{t+k+1} + \frac{2\sigma}{t+1})$ and $N_1 = \gamma k(\frac{8-\sigma^2}{t+1} + \frac{2\sigma}{t+k+1})$, respectively.

Action reaction market

In an action reaction market collaboration will occur if:

1. $h_1 < l_1$
2. $l_2 \geq l_1$
3. $h_2 \geq h_4$

The first requirement $h_1 < l_1$, indicates that the market is an action reaction type. Substituting (3.27) to (3.30), into the expressions for h_1, l_1, and we then get the result that $\alpha \geq \alpha_3$ if $h_1 - l_1$=(3.30)-(3.28)-(3.27)+(3.29)<0.

From requirements 2 & 3 ($l_2 \geq l_1$ & $h_2 \geq h_4$) we have

$$n \leq n_4 = \frac{R_6 - R_1 + C}{C + \theta(x_i + x_j)}; \quad (3.45)$$

$$n \geq n_3 = 1 - \frac{R_6 - R_2}{C + \theta(x_i + x_j)} \quad (3.46)$$

(3.45) and (3.46) jointly suggest that if $\alpha \geq \alpha_3$ then firms may collaborate for n's in the range of $n \in [n_3, n_4]$. In particular, to avoid n's upper bound n_4 being smaller than its lower bound n_3, α must be limited to the range of

$$\alpha \geq \alpha_4 = \frac{M_2^2 + N_2^2 + \frac{\theta G}{t+k+1} - 2G^2}{(8-\sigma^2-2\sigma)\left[2(2G+N_2-M_2) - \frac{\theta}{t+k+1}\right]}.$$

where $M_2 = \gamma(\frac{8-\sigma^2}{t+k+1} + \frac{2\sigma}{t+k})$ and $N_2 = \gamma(\frac{8-\sigma^2}{t+k} + \frac{2\sigma}{t+k+1})$, respectively.

3.5.4.1 When Do Firms Collaborate (Three-Strategy Set)

By considering the three conditions on α, we can now explore the impact of α on firms' responses to see under what circumstance firms will collaborate. Table 3.6 illustrates the required values of α if firms are to collaborate in both persistent dominance and action reaction markets. From the Table 3.6, we see that the requirements upon α are quite stringent and only for a limited range of values will collaboration occur.

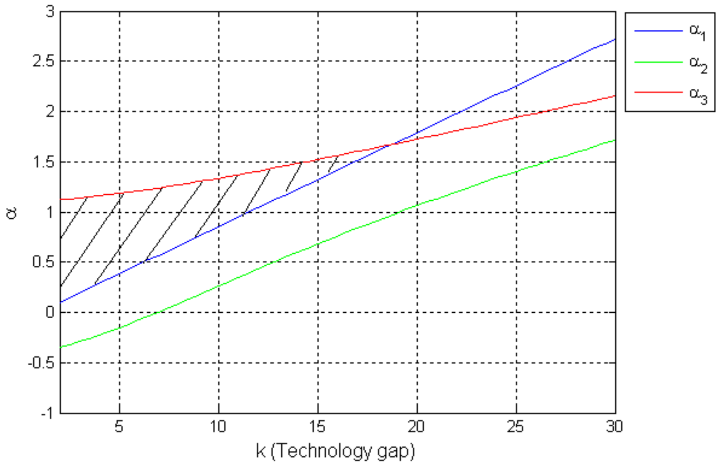
Table 3.6 Required Conditions for Collaboration in Three-Strategy Set

Market condition on α	Explanations
$\alpha > \alpha_1$	Ensures the equilibrium price, equilibrium output and the equilibrium revenue are all positive.
$\alpha \geq \alpha_2$	Ensures $[n_1, n_2]$ is not empty
$\alpha \leq \alpha_3$	Ensures it is a persistent dominance market; otherwise, it is assumed to be an action reaction market
$\alpha \geq \alpha_4$	Ensures $[n_3, n_4]$ is not empty.

According to the table above, in a persistent dominance market the upper bound on α if collaboration is to occur is α_3, whilst the lower bound is $\max(\alpha_1, \alpha_2)$. As the values of α_1, α_2, α_3 vary with the value of other parameters, such as t, k, θ, σ, and β, the border of both the upper bound and lower bound change as these parameters change. To better illustrate this, we employ MATLAB to illustrate how the possibility of collaboration changes as individual parameters change.

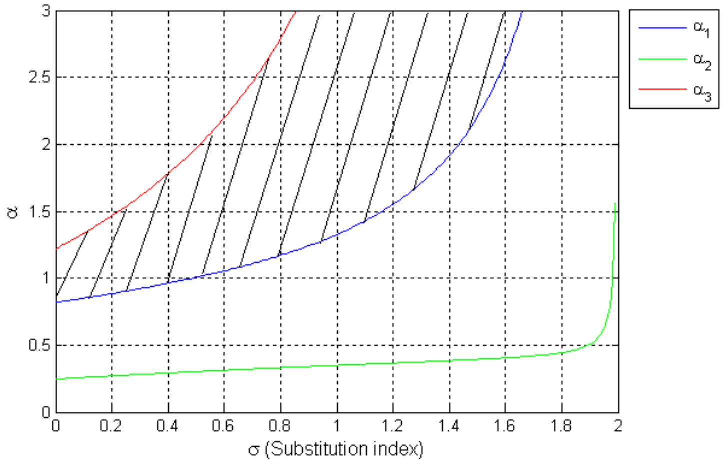
Figure 3.8 illustrates how the possibility of collaboration changes as the technology gap, k, changes in a three-strategy persistent dominance market. The collaboration conditions α_1, α_2, α_3 are represented by blue, green and red line respectively. According to table 3.6, the α will satisfy the conditions for collaboration if it lies above both the green and blue lines but below the red line. As a result, the interior area between the three lines may be regarded as the area where collaboration is possible and any market with such a value for α will exhibit collaboration. From Figure 3.8, we may also observe that increasing the technology gap will decrease the possibility of collaboration eventually to zero. That is to say, if firms' technology gap is bigger than certain level (in this case, it is about $k=17$), firms will not collaborate in a persistent dominance market.

Figure 3.8 Impacts of Technology Gap on Collaboration in a Three-Strategy PD Market



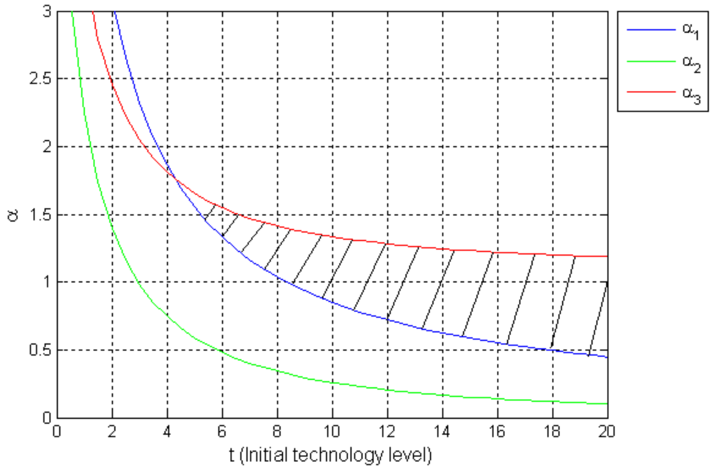
$\sigma=0.1; k=[2,30]; t=10; \gamma=1; \beta=0.5; \lambda=1; \theta=10$

Figure 3.9 Impacts of Substitution Index on Collaboration in a Three-Strategy PD Market



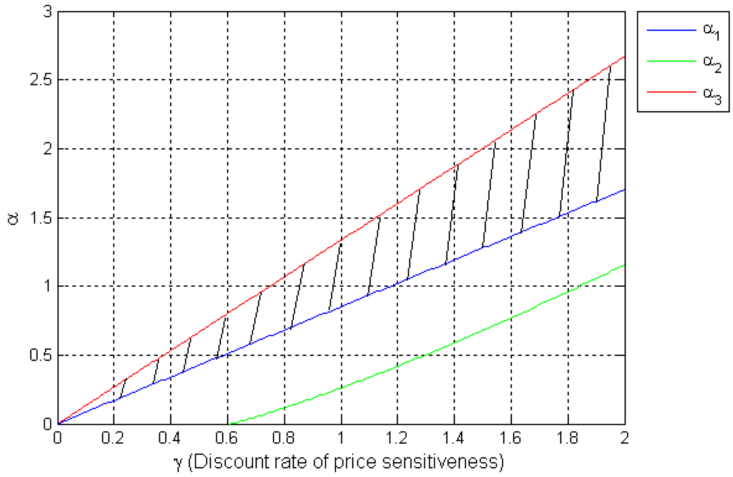
$\sigma = [0,2]; k = 10; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.10 Impacts of Initial Technology Level on Collaboration in a Three-Strategy PD Market



$\sigma = 0.1; k = 10; t = [0,20]; \gamma = 1; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.11 Impacts of Discount Rate of Price Sensitiveness on Collaboration in a Three-Strategy PD Market



$\sigma = 0.1; k = 10; t = 10; \gamma = [0.1,2]; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.9 to 3.11 respectively indicate how the possibility of collaboration in a three-strategy persistent dominance market varies when the substitution index σ, the initial technology level t,and the discount rate of price sensitiveness γ changes. It is clear that in general, increasing σ, t,and γ may increase the possibility of collaboration. In particular, growth in t may cause a change from non-collaboration to collaboration. Firms may not start to consider collaboration as a better option unless their initial technology level reaches a certain level (in this case, it is about $t = 4$).

By combining the findings from figure 3.8 to figure 3.11, we thus claim:

Prediction 3: In a three-strategy persistent dominance market, the probability of collaboration generally increases with the product substitution index, the initial technology level and the discount rate of price sensitiveness, but decreases with the technology gap.

As addressed in section 2.3.6, there is a debate about whether higher transactions costs lead to more or less collaboration. That is because, on one hand, incurring transaction costs is an effective way to avoid the risk that a partner acts opportunistically, improves the transaction process and helps firms to realise the potential rents of collaboration. But on the other hand, since the transaction cost absorbs profit from the collaborative rents, overemphasis on the protective mechanism may reduce the net gain (Madhok & Tallman, 1998). Thus, players face a trade-off between reducing opportunism and increasing returns. Only if the increase in expenditure on transaction cost is less than the incremental rents, yielding a higher net payoff in the post collaboration period, is it worth while investing in any capability that will reduce opportunism. The dilemma is that as result there are no clear predictions on the relationship between the transaction costs incurred and the probability of collaboration.

However, in the three-strategy persistent dominance market, we found that if there is an increase in the value of θ, the green line, then α_2 would drop to a lower level. Since only α_2 contains θ, this would imply that increasing the transaction cost may decrease α_2, but the positions of α_1 and α_3 are unaffected Thus increasing θ may increase the probability of collaboration until α_2 drops to a lower position than α_1. We consequently may state:

Prediction 4: In a three-strategy persistent dominance market, increasing transaction costs will stimulate collaboration until the transaction cost reaches a certain level. When transaction cost is above that level, the chance of collaboration will not be affected by further increases in transaction costs.

Prediction 4 implies that in a persistent dominance market, when the transaction cost level is low, the effect of reducing opportunism from increased transaction cost outweighs the extra cost burden. The net result is a positive relationship between transaction cost and collaboration opportunity. But as transaction costs become large, the incremental rents may not cover extra expenditure on transaction costs, In this case, whether firms' collaborate may be affected by other market characteristics, such as $\alpha, \beta, \lambda, \gamma, \sigma$, but not by transaction cost. Thus prediction 4 indicates that in a three-strategy market the relationship between transaction cost and collaboration is not simple. Whether transaction cost influences collaboration depends upon its level and other market characteristics. This might explain why there is such a long running debate on collaboration and transaction costs in past literatures.

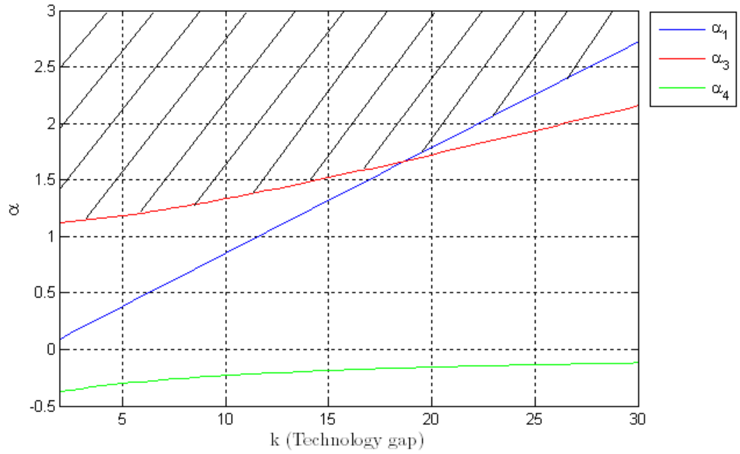
In contrast, according to table 3.6, the conditions on α affecting the probability of collaboration in an action reaction market are $\alpha > \alpha_1, \alpha > \alpha_3$ and $\alpha \geq \alpha_4$, which are respectively represented by blue, red and green lines in the Figures below. In Figures 3.12 to 3.15 we illustrate how the probability of collaboration changes in an action reaction market, when technology gap k, substitution index σ, initial technology level t and discount rate of price sensitiveness γ change. On this basis we claim that:

Prediction 5: In a three-strategy action reaction market, the probability of collaboration generally increases with the initial technology level, but decreases with the technology gap, the product substitution index and the discount rate of price sensitiveness.

Since increasing the transaction cost will further lower the position of α_4, this will loosen the α_4 restriction. However, as both red and blue lines are already far above the green curve, relaxing the condition on α_4 does not bring any greater probability of collaboration. Thus,

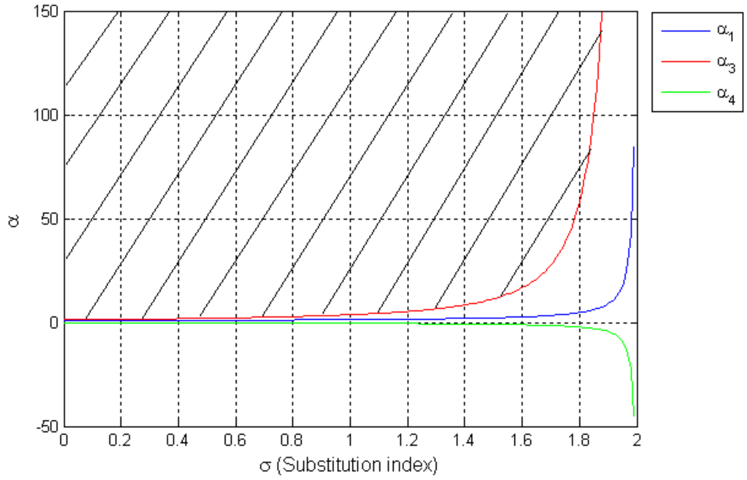
Prediction 6: In a three-strategy action reaction market, increasing transaction cost neither encourages nor diminishes the probability of collaboration.

Figure 3.12 Impacts of Technology Gap on Collaboration in a Three-Strategy AR Market



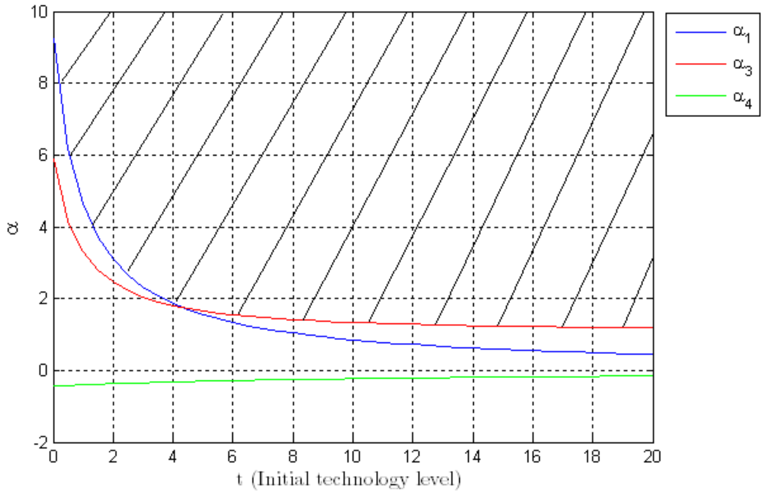
$\sigma = 0.1; k = [2{,}30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.13 Impacts of Substitution Index on Collaboration in a Three-Strategy AR Market



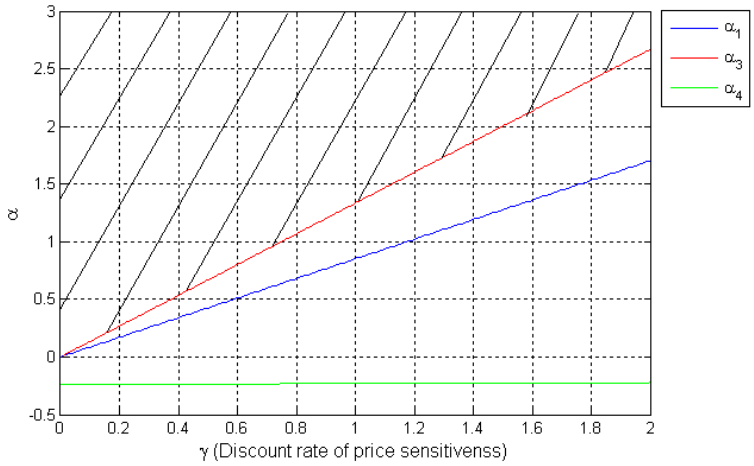
$\sigma = [0{,}2]; k = 10; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.14 Impacts of Initial Technology Level on Collaboration in a Three-Strategy AR Market



$\sigma = 0.1; k = 10; t = [0{,}20]; \gamma = 1; \beta = 0.5; \lambda = 1; \theta = 10$

Figure 3.15 Impacts of Discount Rate of Price Sensitiveness on Collaboration in a Three-Strategy AR Market



$\sigma = 0.1; k = 10; t = 10; \gamma = [0,2]; \beta = 0.5; \lambda = 1; \theta = 10$

3.5.4.2 Sharing Costs under Collaboration (Three-Strategy Set)

Apart from the issue of whether firms will collaborate we are also interested in how the (R&D) costs will be shared when they collaborate. For values for α in the shaded firms prefer collaboration rather than competition, and there may be differing cost sharing rules that are consistent with these values. The firms in fact have various possibilities of cost sharing. As long as α stays in the interior area, any $n \in [n_1, n_2]$ (in a persistent dominance market) or $n \in [n_3, n_4]$ (in an action reaction market) could generate the greatest net payoff to both firms from collaboration. However, what is the best cost sharing plan of n in the range of $[n_1, n_2]$ or $[n_3, n_4]$? Could transaction costs push both firms to negotiate on a fixed cost equilibrium agreed by both players?

Such questions mainly concern cost or profit sharing or cost or profit allocation issues. These are generally solved in cooperative games by using one of two solutions, the Shapley value solution and Nash bargaining solution (Mcginty, 2007). To use a Shapley solution two conditions must be met. First, the value of collaboration must be non-negative; second, the joint collaboration cost must be smaller than choosing non-collaboration, which is called superadditivity (Krajewska et al, 2008; Kaitala et al, 1995; Mcginty, 2007).As shown in our model, $\alpha \geq \alpha_1$ satisfies the first condition. However, since collaboration cost contains both positive R&D cost and transaction cost, the joint value of the collaboration cost may be non-smaller than choosing non-collaboration strategies. Thus, we prefer to employ the Nash bargaining solution when dealing with the collaboration cost sharing problem, (which also helps the joint collaboration organisation to reach Pareto efficiency).

Suppose the collaboration cost equilibrium can only be reached where the players' joint net payoff is maximized (Dow, 1985). The net payoffs (NP_i) for both players (which differ from the incentive functions) in both a persistent dominance market and an action reaction market, are measured by:

$$NP_H = R_6 - (1-n)(C + \theta(x_i + x_j)) \quad \text{for H} \tag{3.47}$$

$$NP_L = R_6 - n(C + \theta(x_i + x_j)) \quad \text{for L} \tag{3.48}$$

To optimize the value of the joint net payoff, we take first order condition for $NP_H * NP_L$ by substituting the value of post collaboration payoff function (3.32).

$$\frac{\partial(NP_H * NP_L)}{\partial n} = (C + \theta(x_i + x_j))^2 - 2n(C + \theta(x_i + x_j))^2 = 0 \tag{3.49}$$

The second order condition on the maximisation requires that

$$-2(C + \theta(x_i + x_j))^2 < 0 \tag{3.50}$$

The convex curve for the joint payoff guarantees that its optimal value is reached when $n = 0.5$, showing the optimal cost percentage for firm L is to pay 50% when both firms agree to collaborate. However, since the acceptable range of cost coefficient n for collaboration may exclude $n = 0.5$, firms could also negotiate to collaborate when $n \in [n_1, n_2]$ or $n \in [n_3, n_4]$. In this case, since the second order of joint payoff is strictly negative, the maximum value of $NP_H * NP_L$ may be calculated upon the critical value of $[n_1, n_2]$ or $[n_3, n_4]$.

Proposition 1. If a three-strategy market allows persistent dominance behaviour under competition, firms will collaborate when the collaboration cost for L satisfies:

$$n = \begin{cases} n_1, \text{ if } n_1 > 0.5 \\ 0.5 \\ n_2, \text{ if } n_2 < 0.5 \end{cases}$$

Proposition 2. If a three-strategy market allows action reaction behaviour under competition, firms will collaborate when the collaboration cost for L satisfies:

$$n = \begin{cases} n_3, \text{ if } n_3 > 0.5 \\ 0.5 \\ n_4, \text{ if } n_4 < 0.5 \end{cases}$$

Table 3.7 Conditions of Collaboration Cost in a Three-Strategy Market

Range of α	**Market Type**	**Range of n**	**Sub-range of n**	n
$(-\infty, \max(\alpha_1, \alpha_2))$	$h_1 > l_1$ (PD)	No Collaboration		
$[\max(\alpha_1, \alpha_2), \alpha_3]$	$h_1 > l_1$ (PD)	$[n_1, n_2]$	$n_1 > 0.5$	$n = n_1$
			$n_1 \le 0.5 \le n_2$	$n = 0.5$
			$n_2 < 0.5$	$n = n_2$
$(\alpha_3, \max(\alpha_3, \alpha_4))$	$h_1 < l_1$ (AR)	No Collaboration		
$[\max(\alpha_3, \alpha_4), +\infty)$	$h_1 < l_1$ (AR)	$[n_3, n_4]$	$n_3 > 0.5$	$n = n_3$
			$n_3 \le 0.5 \le n_4$	$n = 0.5$
			$n_4 < 0.5$	$n = n_4$

The table above combines the collaboration conditions on α in Table 3.6 and proposition 1 & 2, showing precisely in what circumstance firms collaborate and the share of the collaboration cost that needs to be paid by the technology follower L. The first row of conditions in table 3.7 shows that in a persistent dominance market, there is no collaboration unless the market allows a positive price, output and revenue and existence of a collaboration cost sharing plan possibilities. The second row indicates that in a persistent dominance market, only a market with α which satisfies $\alpha > \alpha_1$, $\alpha \geq \alpha_2$ and $\alpha \leq \alpha_3$ will allow firms to collaborate. In particular, when firms collaborate, the transaction cost would push negotiable collaboration cost to an equilibrium which follows the rules in proposition 1. When $\alpha \geq \alpha_3$ the market type would change from persistent dominance market to action reaction. In particular, if α is in a range of $(\alpha_3, \max(\alpha_3, \alpha_4))$, then the negotiable collaboration cost set for firms is empty, indicating that there exists no proper collaboration cost sharing plan when firms collaborate. Another feature we observe is that if α reaches the point of $\max(\alpha_3, \alpha_4)$ or above, both firms will prefer collaboration and the way to share collaboration cost will depend upon proposition 2.

We may now state two further predictions.

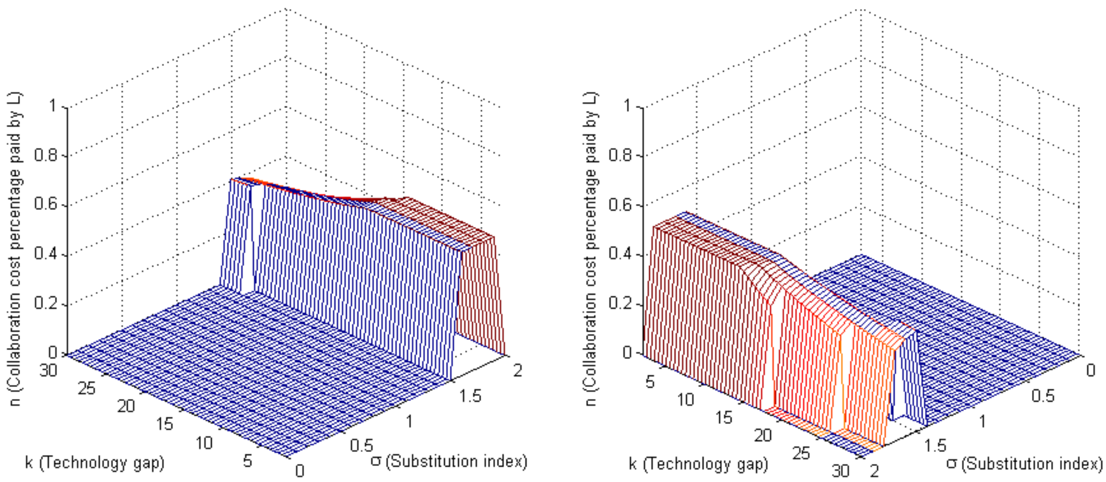
Prediction 7: Increasing the value of α may cause the market structure to change from persistent dominance to action-reaction.

Prediction 8: When α is small, neither firm will wish to collaborate even though they have the chance to do so. Firms will collaborate only when α is above a certain level.

On the other hand, it is clear to see that in each market type, the collaboration cost equilibrium actually contains three sub-equations. This would make our analysis excessively complicated if we discussed the three sub-equations separately. We therefore use MATLAB to simulate the collaboration cost percentage function rather than explore first order differentiation of each parameter. In fact, as the first and second order of differentiation for some parameters are not constantly positive or negative, it is almost impossible to conclude on each parameter's potential impact. Since the MATLAB programme allows the value of n to pick the very sub-equation automatically when n matches its corresponding requirements, we are not required to calculate the complex implications of changes in the collaboration cost percentage equation. Instead, we observe how the collaboration cost equilibrium changes as we shift the value of each individual parameter. 3-D figures enable us to discuss the impacts of two parameters at one time. As we are interested in four parameters, two sets of 3-D figures may be needed. In each set of 3-D figures, two graphics captured from different angles are provided. We first look at how the collaboration cost percentage changes in a persistent dominance market, then move to an action reaction market.

Figure 3.16 suggests how the collaboration cost percentage changes in a three-strategy persistent dominance market, if we change substitution index σ and the technology gap k. The figures only cover cases where the value for α makes collaboration feasible.

Figure 3.16 Impacts of Technology Gap and Substitution Index on Collaboration Cost in a Three-Strategy PD Market when Collaboration is Feasible

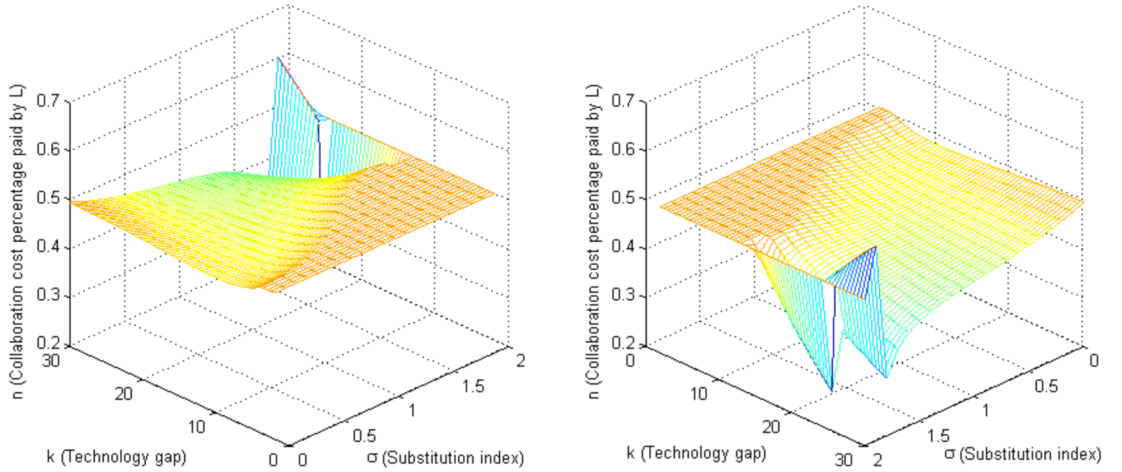


$$\sigma = [0,2]; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$$

In Figure 3.16, we notice that the collaboration cost percentage paid by L drops dramatically at some points, indicating the cost percentage in that state is zero. This is because the applied α is out of the acceptable range. In other words, the figure above only shows the left image from the original collaboration cost percentage map integrated with the collaboration condition maps. For instance, as shown in figure 3.8 and figure 3.9, with conditions that $\sigma = 0.1$, $k = 10$, $t = 10$, $\gamma = 1$, $\beta = 0.5$, $\lambda = 1$, $\theta = 10$, firms may choose collaboration when $\alpha = 0.8$ to 1.4. But the value of α given from the market is 15. That means no collaboration activity is preferred, so we consequently cannot observe the general trend of collaboration cost if they do choose collaboration when the fitted market parameter is feasible. Thus, adding collaboration conditions into collaboration cost selection models gives us an illusion that the collaboration cost paid by firm L is dramatically low. To avoid this problem, we need to take the cap of collaboration conditions off from both collaboration cost selection models and collaboration cost figures. Therefore, all the figures relating to collaboration cost percentages below are drawn regardless of the impact of collaboration conditions and are generated only with the original collaboration selection models.

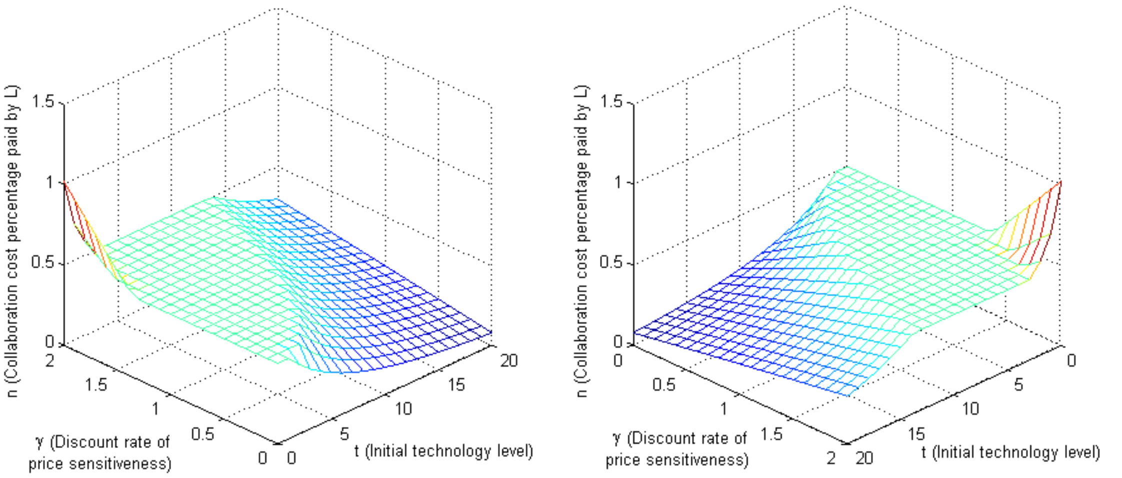
Figure 3.17 below describes how the collaboration cost percentage changes in a three-strategy persistent dominance market, if we change the substitution index and technology gap , whilst Figure 3.18 below suggests how collaboration cost percentage in three-strategy persistent dominance market moves if we change initial technology level and perceived price index . In fact, we have tested a number of collaboration cost percentage functions by substituting different value ranges. Beyond the different values obtained for , all their shapes are the same.

Figure 3.17 Impacts of Technology Gap and Substitution Index on Collaboration Cost in a Three-Strategy PD Market



$\sigma=[0,2]; k=[2,30]; t=10; \gamma=1; \beta=0.5; \lambda=1; \alpha=15; \theta=10$

Figure 3.18 Impacts of Initial Technology Level and Discount Rate of Price Sensitiveness on Collaboration Cost in a Three-Strategy PD Market



$\sigma=0.1; k=10; t=[0,20]; \gamma=[0.1,2]; \beta=0.5; \lambda=1; \alpha=15; \theta=10$

From these figures, we find that increasing σ decreases the collaboration cost percentage n initially but gradually starts to increase it. At a certain point with a high substitution level, σ explodes implying a high collaboration cost percentage. This result suggests that in general, the greater is product substitution, the less is the portion of collaboration costs that firm L will pay. But in a market with similar products, increasing product substitution would results in a greater collaboration cost portion paid by L. On the other hand, increasing k normally decreases the collaboration cost percentage n. This result indicates in general, that a greater technology gap decreases the collaboration cost portion paid by L.

From Figure 3.18 we find that increasing the initial technology level t rapidly decreases the collaboration cost percentage paid by L until it reaches 50% where it stays no matter how t or γ further change. However, n would decrease gradually if we keep increasing t. On the other hand, increasing the discount rate of price sensitiveness, γ, would first gradually increase the collaboration cost percentage until it reaches 50%. But n increases quickly with γ once n exceeds the 50% platform. This result indicates the fact that in general, increases in the initial technology level diminishes the firm L's collaboration cost percentage, whilst the discount rate of price sensitiveness increases it.

It is clear from Figure 3.17 & 3.18 that the collaboration cost share paid by L varies from 0 to any positive value, which means that in a persistent dominance market, the low technology firm must pay when it collaborates. In particular, we notice the percentage paid by L could even exceed 100% in extreme cases when the transaction cost is small enough (for instance when $\theta = 1$). This result indicates that, in some rare circumstances, the high-technology firm pays nothing but could even receive an extra payoff just for agreeing to collaboration from his rival who is keen to launch new technology![2]

[2] Beyond the variable parameters' values from different markets, we found that the rare case where the low technology firm pays more than 100% only occurs when the product substitution index is extremely high or/and the initial technology level is very low. That means that collaboration on a product with a high substitution index or/and a low initial technology level might occur in rare cases. An example of such a situation may be petroleum exploitation collaboration between foreign enterprises and the China

Similar idea has been supported by Rosenkranz (1995) who advocates that the player may receive extra side payments from his rival for collaboration.

Therefore, based on the information obtained from above figures, two more predictions are generated for a persistent dominance market.

Prediction 9: In a three-strategy persistent dominance market, the collaboration cost percentage paid by the lower technology firm generally increases with the discount rate of price sensitiveness, but decreases with increases in the technology gap, the product substitution index and the initial technology level. However in a market with highly similar products, the collaboration cost percentage paid by the lower technology firm increases with the product substitution index.

Prediction 10: Under a three-strategy persistent dominance market structure, if firms collaborate, the firm with the lower technology level must pay. As to the percentage he pays, this depends upon the nature and market structure of both firms. However, in rare cases, the percentage could exceed 100%.

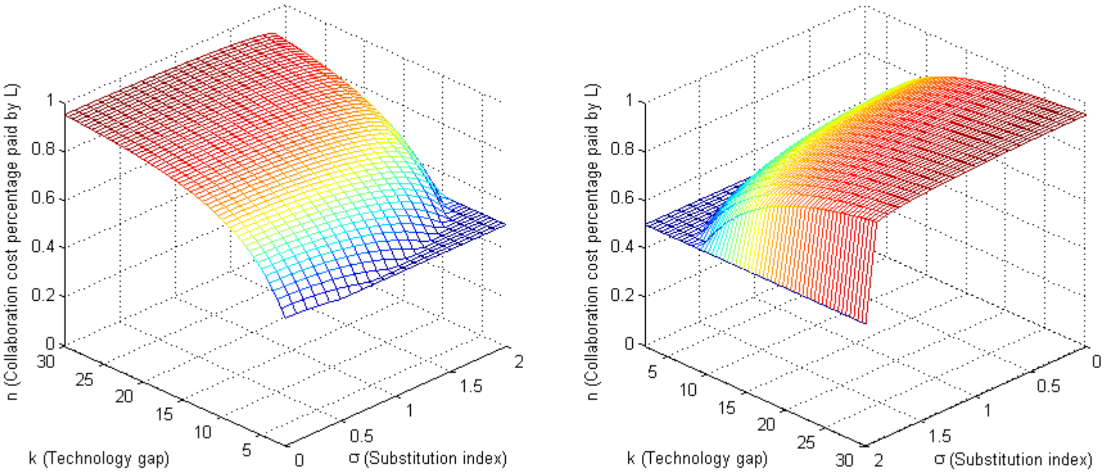
National Offshore Oil Corporation (which by law is the single firm responsible for the overall business of exploiting offshore petroleum resources in the People's Republic of China in cooperation with foreign enterprises since the 1980s and thus this is a case of a three-strategy market in which the possibility of imitation is ruled out). Article 8 of the *'Regulations of the People's Republic of China on Exploitation of Offshore Petroleum Resources in Cooperation with Foreign Enterprises' (*http://english.gov.cn*),* states that:

'…the foreign enterprise party to the petroleum contract … shall provide the investment to carry out prospecting, be responsible for prospecting operations and bear all prospecting risks; after a commercial oil (gas) field is discovered, both the foreign contractor and the China National Offshore Oil Corporation shall provide the investment for its cooperative development….'

This regulation clearly shows that the foreign party has to bear all exploitation cost in the collaboration before an oil (gas) field is discovered. If we take pre-collaboration cost (hidden cost by Teece, 1986; Ergun et al, 2007) into account, such as transaction cost, the foreign party therefore may bear more than 100% of exploration costs.

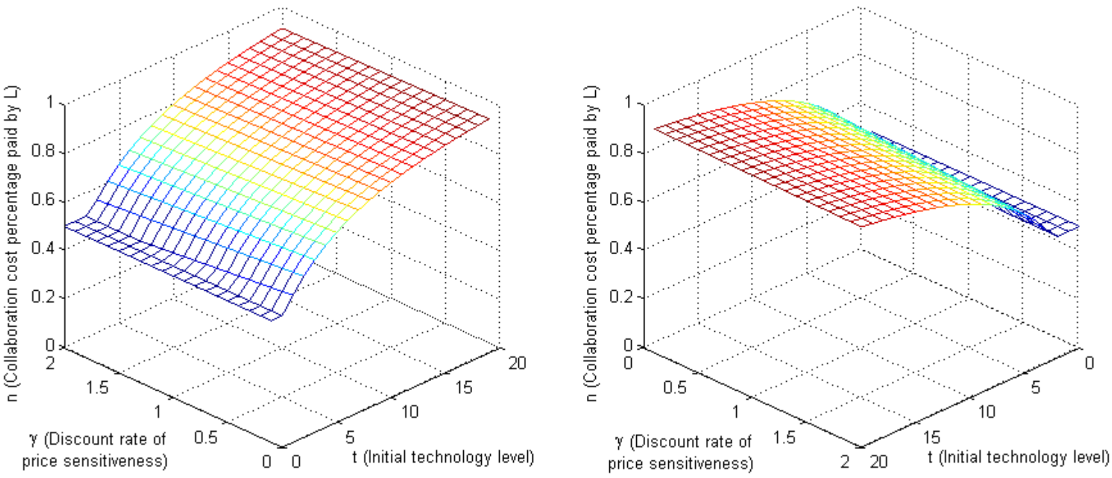
In contrast, the cost paid by the lower technology firm in a situation of collaboration in an action reaction market is shown by figures 3.19 & 3.20. Similar to the analysis in a persistent dominance market, the first two graphics represent how collaboration cost changes in a three-strategy action reaction market when the substitution index and technology gap change, whilst the other two graphics indicate the impacts of initial technology level and perceived price index on collaboration cost.

Figure 3.19 Impacts of Substitution Index and Technology Gap on Collaboration Cost in a Three-Strategy AR Market



$\sigma = [0,2]; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

Figure 3.20 Impacts of Initial Technology Level and Discount Rate of Price Sensitiveness on Collaboration Cost in a Three-Strategy AR Market



$\sigma = 0.1; k = 10; t = [0,20]; \gamma = [0.1,2]; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

As clearly shown in Figure 3.19, increases in σ result in the gradual decrease of n until n reaches 50%, whilst increases in k lead to the growth of n starting from $n=0.5$. We therefore claim that in a three-strategy action reaction market, the collaboration cost percentage paid by firm L increases with the technology gap, but decreases with the substitution index.

From Figure 3.20, we find that an increase in t consistently increases n, whilst an increase in the discount rate of price sensitiveness γ, slightly reduces the level of n. In particular, the lowest percentage firm L pays in an action reaction market is 50%. This finding shows that the collaboration cost proportion paid by firm L in an action reaction market increases with the initial technology level but decreases with the perceived price index.

In addition, even although n may decrease rapidly at a lower level of t, its value still keeps above 0.5, indicating that in an action reaction market, when firms collaborate, the lower technology firm always pays the bigger proportion of the cost. That may be explained by the argument that since firm L definitely wins the competition in an action reaction market, even a small contribution to costs by his rival is welcome. Again, based on the information obtained from the above figures, two further predictions in an action reaction market are therefore generated.

Prediction 11: In a three-strategy action reaction market, the collaboration cost percentage paid by the lower technology firm generally increases with the technology gap and the initial technology level, but slightly decreases with increases in the product substitution index and the discount rate of price sensitiveness.

Prediction 12: In a three-strategy action reaction market, if firms collaborate, the firm with the lower technology level must pay more than 50% of the R&D cost.

3.5.5 The Four-Strategy Set

We now allow that an extra endogenous imitation strategy is available to firms and here reconsider the whole game framework by investigating the impact upon the probability of collaboration and the allocation of R&D costs and transaction cost in the new equilibrium.

Persistent dominance market

According to situation I in Table 3.5, the conditions that must be met for collaboration to occur in a persistent dominance market in the four-strategy case are:

1. $h_1 > l_1$
2. $h_2 \geq h_1$
3. $l_2 \geq l_4$
4. $l_2 \geq l_3$

Comparing with the three-strategy case, it is clear that an extra requirement (4) is added which requires that firms must obtain a higher return through collaboration than imitation. By substituting from equations (3.31) and (3.32), the new collaboration cost restriction that meets the condition that $l_2 \geq l_3$ is

$$n \leq \frac{R_6 - R_5 + (1-\phi)C}{C + \theta(x_i + x_j)} = n_5 \text{, where } \phi = \frac{\mu}{\left|u_i - u_j\right|} = \frac{\mu}{k-1};\ 0 < \mu < 1 \qquad (3.51)$$

n_5, therefore, is the new upper bound on the collaboration cost paid by L in a persistent dominance market. It must be also bigger than the lower bond n_1

, if the collaboration cost sharing set is not to be empty. Satisfying $n \in [n_1, n_2] \bigcap [n_1, n_5]$ generates an additional restriction on α if collaboration is to occur when imitation is feasible, this being,

$$\begin{cases} \alpha \leq \alpha_5 = \dfrac{(M_1^2 + \dfrac{\theta G}{t+k+1} - 2G^2 - C^I)}{(8-\sigma^2-2\sigma)\left[2(2G-M_1) - \dfrac{\theta}{t+k+1}\right]} \quad \text{when } \alpha_5 \geq 0; \\ \text{OR} \\ \alpha > \alpha_5 = \dfrac{(M_1^2 + \dfrac{\theta G}{t+k+1} - 2G^2 - C^I)}{(8-\sigma^2-2\sigma)\left[2(2G-M_1) - \dfrac{\theta}{t+k+1}\right]} \quad \text{when } \alpha_5 < 0; \end{cases} \tag{3.52}$$

Function sets (3.52) implies the newly added restriction from imitation, α, is smaller than α_5 if α_5 is bigger than zero or is larger than α_5 if α_5 is smaller than zero. Similarly, in action reaction market, we may have

Action reaction market

In an action reaction market with imitation, if collaboration is to occur we similarly require that:

1. $h_1 < l_1$
2. $l_2 \geq l_1$
3. $h_2 \geq h_4$
4. $h_2 \geq h_3$

The additional restriction (4) indicates that with imitation as a possible strategy, collaboration will only acquire if the incentive for firm H to collaborate is no smaller than the incentive to imitate, i.e. $h_2 \geq h_3$. This means,

$$n \geq 1 - \frac{R_6 - R_5 + (1-\phi)C}{C + \theta(x_i + x_j)} = n_6 \text{, where } \phi = \frac{\mu}{|u_i - u_j|} = \frac{\mu}{k-1}\text{; } 0 < \mu < 1 \tag{3.53}$$

For the range of possible collaboration cost shares to not be empty requires that $n \in [n_3, n_4] \bigcap [n_{6,} n_4]$ which adds another restriction on α that must be met if collaboration is to occur i.e.

$$\alpha \geq \alpha_6 = \frac{(M_2^2 + \frac{\theta G}{t+k+1} - 2G^2 - C^I)}{(8-\sigma^2-2\sigma)\left[2(2G - M_2) - \frac{\theta}{t+k+1}\right]} \tag{3.54}$$

3.5.5.1 When Do Firms Collaborate (Four-Strategy Set)

The four conditions that α must satisfy if collaboration is to occur are summarized in Table 3.8.

Table 3.8 Required Conditions for Collaboration in a Four-Strategy Set

Market condition on α	**Explanations**
$\alpha > \alpha_1$	Ensure the equilibrium price, equilibrium output and the equilibrium revenue are all positive.
$\alpha \geq \alpha_2$	Ensure $[n_1, n_2]$ is not empty
$\alpha \leq \alpha_3$	Ensure it is persistent dominance market; otherwise, it is assume to be action reaction market
$\alpha \geq \alpha_4$	Ensure $[n_3, n_4]$ is not empty.
$\alpha \leq \alpha_5$ if $\alpha_5 \geq 0$	Ensure $[n_1, n_5]$ is not empty
$\alpha > \alpha_5$ if $\alpha_5 < 0$	
$\alpha \geq \alpha_6$	Ensure $[n_6, n_4]$ is not empty

Looking first at the probability of collaboration in a persistent dominance market, the upper bound of α is $\min(\alpha_3, \alpha_5)$, whilst the lower bound is $\max(\alpha_1, \alpha_2)$. As the value of α_1, α_2, α_3 and α_5 varies with the value of other parameters, such as t, k, θ, σ, and β, the values of both the upper bound and lower bound will change as the three parameters change.

In order to illustrate the impact of the imitation condition we have modified our previous MATLAB exercises to include curves representing α_5. We draw two curves for α_5, representing limiting values for the spillover index

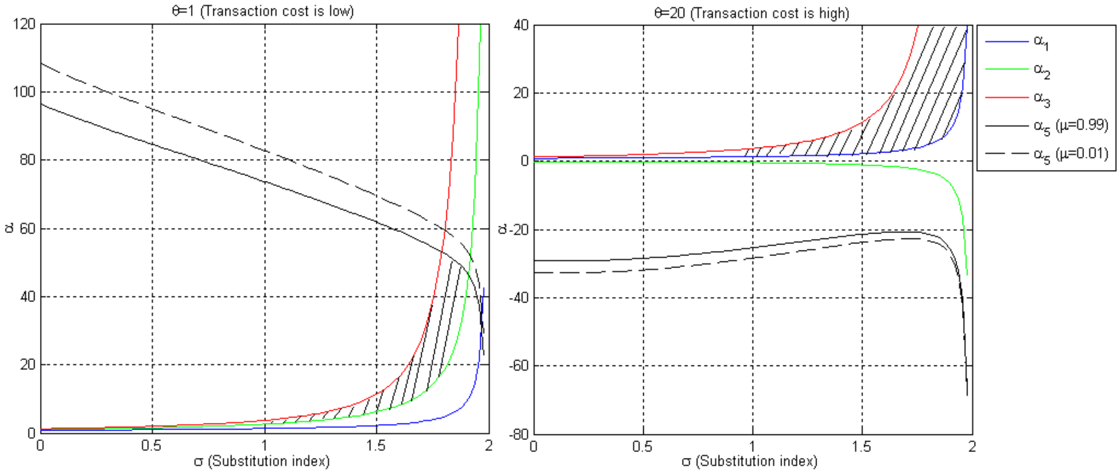
μ of $\mu = 0.01$ represented by black dash curve and $\mu = 0.99$ marked by black curve.

In particular, as the range of α_5 varies with the value of transaction cost θ we may explore the impacts of all parameters upon the level of transaction cost. To be explicit, we discuss each situation when the transaction cost is low ($\theta = 1$) and when the transaction cost is large ($\theta = 20$), respectively. Thus, different from figures in the three-strategy section above, all the following figures are illustrated with two transaction cost groups. In each group, two spillover index curves are represented and two extents of imitation sizes as well.

Figure 3.21 shows how the possibility of collaboration changes as the product substitution index σ increases when imitation is allowed. As should be clear, when the transaction cost level is low, the curve α_5 representing the restriction on the probability of collaboration decreasing from the possibility of imitation, cuts the area located between the red curve and green curve into two halves. According to Table 3.8, only if α is smaller than α_5 (when $\alpha_5 \geq 0$) is there any probability of collaboration. Thus, only in markets with α located in the area defined by the black, red and green curves are collaboration probable.

However, in a market with large transaction cost, we found the value of α_5 lies far below the blue curve α_1. This indicates that introducing the extra strategy, imitation, does not actually influence the chance of collaboration. Indeed, deceasing the spillover effect tends to raise the black curve along with growth of imitation, but it is still far away from affecting the firms' collaboration decision.

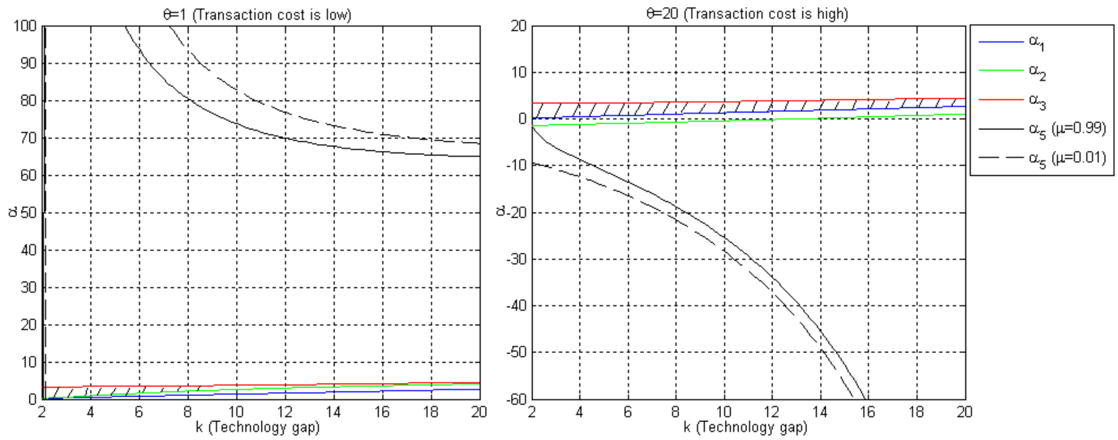
Figure 3.21 Impacts of Substitution Index on Collaboration in a Four-Strategy PD Market



$\sigma = [0,2]; k = 10; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1$

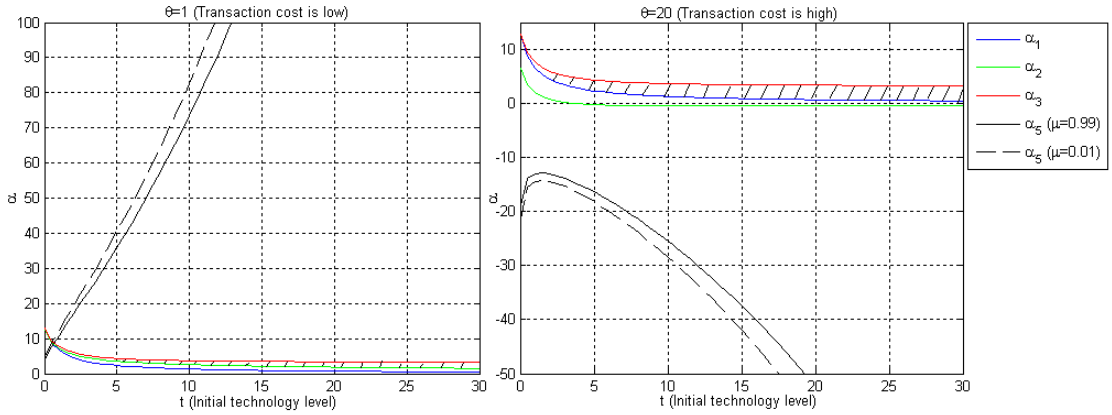
Similarly, Figures 3.22 to 3.24 indicate how the probability of collaboration in a four-strategy persistent dominance market changes when the technology gap k, the initial technology level t ,and the discount rate of price sensitiveness γ change. We observe that adding imitation α_5 into a four-strategy set does not further change the positions of α_1 (blue curve) α_2 (green curve) and α_3 (red curve) from that found under a three-strategy set. Therefore, the predictions concerning the relationship between transaction cost and collaboration remain identical to what we predicted in the three-strategy set case. Prediction 4 may consequently be modified as follows:

Figure 3.22 Impacts of Technology Gap on Collaboration in a Four-Strategy PD Market



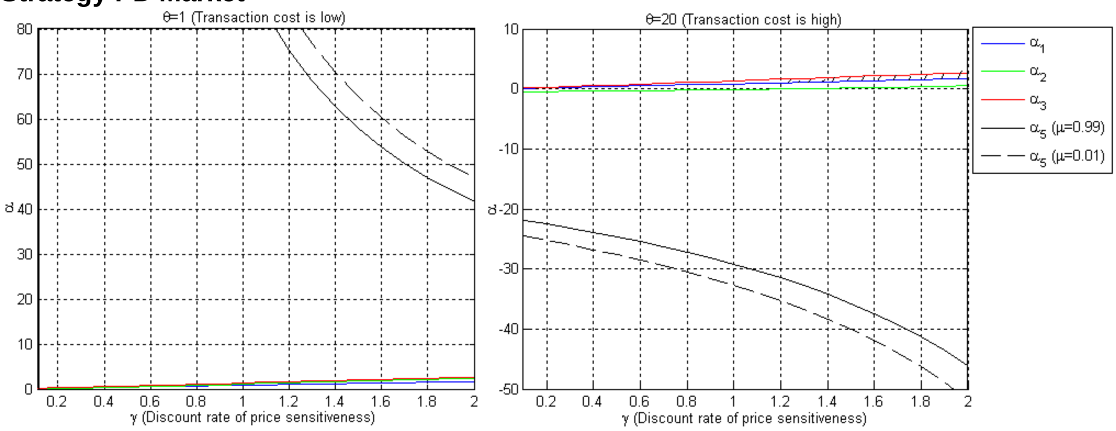
$\sigma = 1; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1$

Figure 3.23 Impacts of Initial Technology Level on Collaboration in a Four-Strategy PD Market



$\sigma = 1; k = 10; t = [0,30]; \gamma = 1; \beta = 0.5; \lambda = 1$

Figure 3.24 Impacts of Discount Rate of Price Sensitiveness on Collaboration in a Four-Strategy PD Market



$\sigma = 0.1; k = 10; t = 10; \gamma = [0.1,2]; \beta = 0.5; \lambda = 1$

Prediction 4: Regardless of whether there are three or four strategies, in a persistent dominance market, increasing transaction costs will stimulate collaboration until the transaction cost reaches a certain level. When transaction cost is over that level, the chance of collaboration will not be affected by further increases in transaction costs.

We are particularly interested in whether collaboration is more likely after imitation is added into the strategy set. Since the curve α_5 is far above the other three curves in these three figures (Figure 3.22—3.24) when transaction cost is low, whilst α_5 is far below $\alpha_1, \alpha_2, \alpha_3$, it seems that if there is a positive probability of collaboration in three-strategy case, adding the extra option, of imitation will make little difference. However we do note that increases in t from a low level when transaction cost is low, may lead (Figure 3.23) the outcome to change from non-collaboration to collaboration. This means that firms in a market with low transaction cost level, may not consider collaboration because imitation provides them a greater net payoff, unless their initial technology level reaches a certain level (in this case, it is about $t=1$).

By combining the findings from figure 3.21 to 3.24, we claim:

Prediction 13: In a four-strategy persistent dominance market, where the transaction cost is low, adding the option of imitation would decrease the probability of collaboration when the product substitution index is high or the initial technology level is low, where firms in both situations may prefer to imitate rather than collaborate.

Moreover, we notice that increasing the spillover index from the position reflected by the black dash curve to the black curve, will result in a decrease of α_5 in all the situations when transaction cost is low. Reducing α_5 intensifies the effects set down in Prediction 13. Thus, we claim,

Prediction 14: In a four-strategy persistent dominance market, where transaction cost is low, increasing the size of imitation will further decrease the collaboration opportunity when the product substitution index is high or the initial technology level is low.

On the other hand, all figures from 3.21 to 3.24 also show that when transaction cost is large, even though increasing the spillover index will lead to a greater α_5, the chance of collaboration remains the same as with the three-strategy set. Thus, we have,

Prediction 15: In a four-strategy persistent dominance market, where transaction cost is high, increasing the size of imitation will neither stimulate nor decrease the collaboration opportunity.

To explain why collaboration opportunity is not influenced by allowing for imitation we need to look into why firms choose collaboration instead of other strategies. In fact, the only reason that firms collaborate in our model is that the net payoff from collaboration is greater than from other strategies. In a four-strategy market, introducing imitation will allow the possibility to launch new technology with lower costs. For those firms in a market with low transaction cost, their decisions are more elastic and vulnerable to cost change. Thus, increasing imitation in that situation may significantly decrease collaboration opportunities so that firms may change their minds and choose imitation rather than collaboration. On the other hand, if firms decide to collaborate with high transaction costs the net payoff from collaboration must far outweigh the gains from other strategies. The attraction of imitation therefore may not seem to be as desirable as it is in a market with low transaction cost.

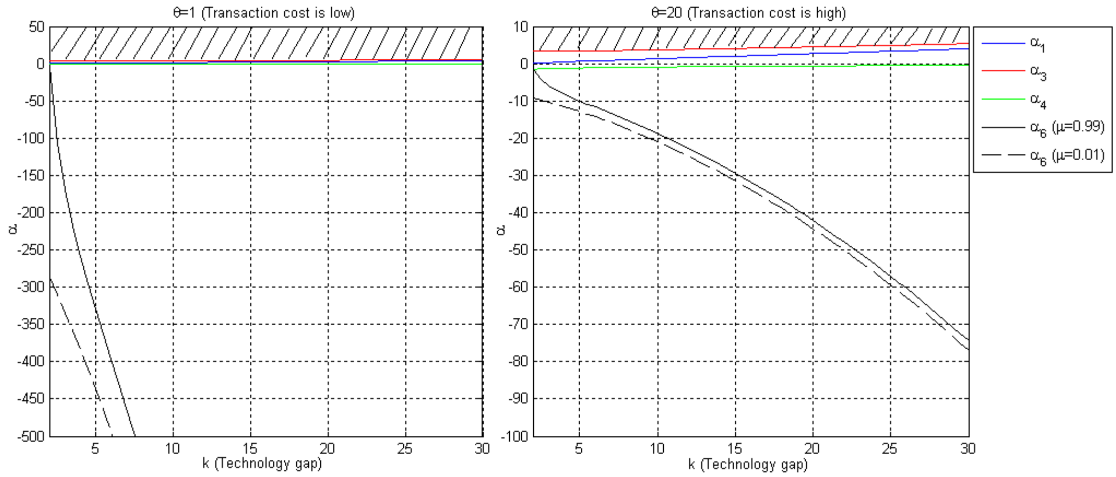
In contrast, according to Table 3.8, the collaboration restrictions on α in an action reaction market are $\alpha > \alpha_1$, $\alpha > \alpha_3$, $\alpha \geq \alpha_4$,and $\alpha \geq \alpha_6$ which are respectively represented by blue, red, and green lines and black curves in the following figures. Figures 3.25 to 3.28 illustrate how the probability of collaboration varies in a four-strategy action reaction market, when technology gap k, substitution index σ, initial technology level t and discount rate of price sensitiveness γ change. Similar to prediction 4, taking imitation into account does not differ the relationship between collaboration and transaction cost in four-strategy action reaction market. Thus, we may rewrite prediction 6 to better fit action reaction market in both strategy-sets.

Prediction 6: Regardless of whether there are three or four strategies, in an action reaction market, increasing transaction cost neither encourages nor diminishes the probability of collaboration.

Besides, the figures in four-strategy action reaction market also show that the extra restriction that $\alpha \geq \alpha_6$, introduced by allowing imitation, is generally not binding and thus allowing imitation in an action reaction market does not influence firms' decisions on collaboration. Therefore,

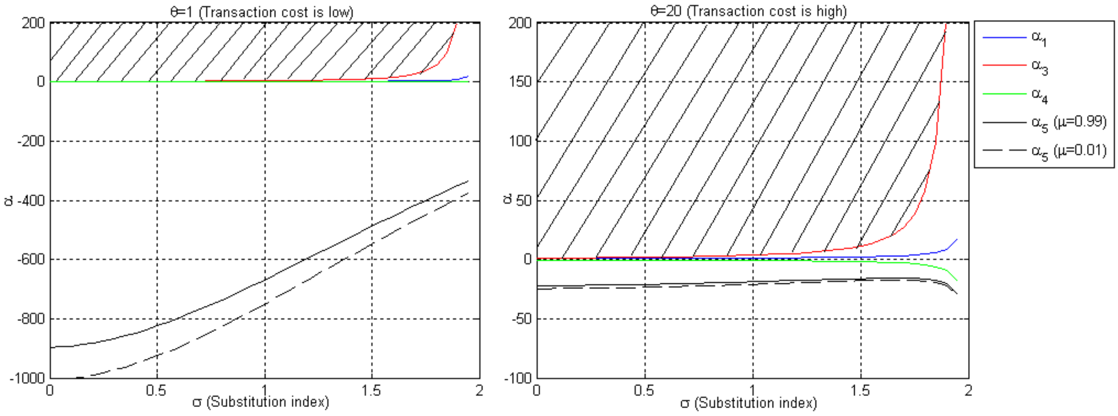
Prediction 16: In a four-strategy action reaction market, the probability of collaboration by firms does not differ from when imitation is feasible.

Figure 3.25 Impacts of Technology Gap on Collaboration in a Four-Strategy AR Market



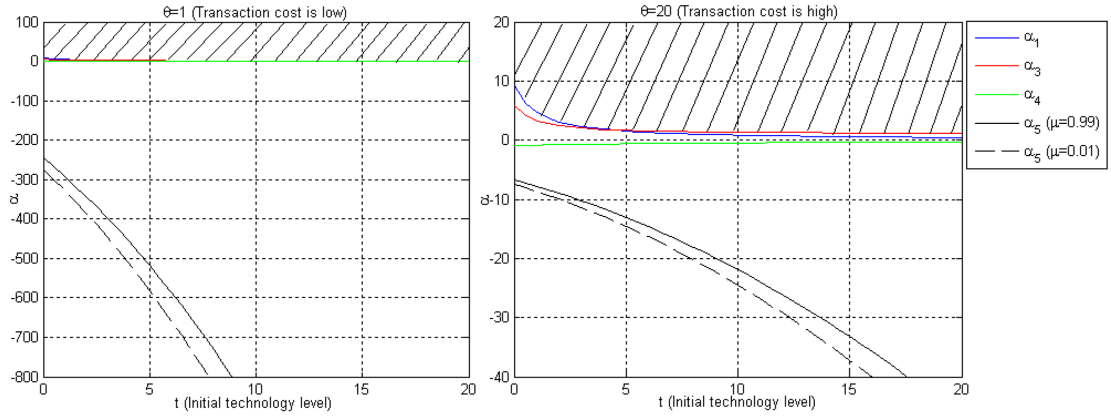
$\sigma = 0.1; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1$

Figure 3.26 Impacts of Substitution Index on Collaboration in a Four-Strategy AR Market



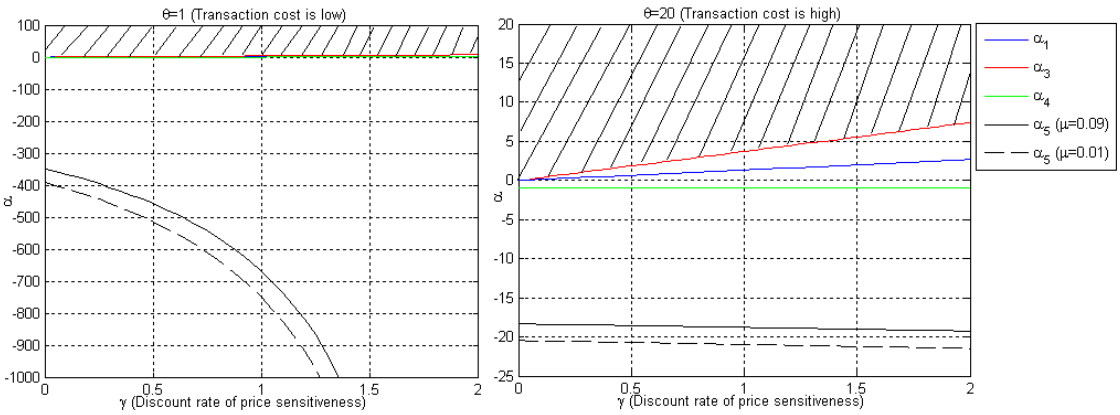
$\sigma = [0,2]; k = 10; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1$

Figure 3.27 Impacts of Initial Technology Level on Collaboration in a Four-Strategy AR Market



$\sigma = 0.1; k = 10; t = [0,20]; \gamma = 1; \beta = 0.5; \lambda = 1$

Figure 3.28 Impacts of Discount Rate of Price Sensitiveness on Collaboration in a Four-Strategy AR Market



$\sigma = 0.1; k = 10; t = 10; \gamma = [0,2]; \beta = 0.5; \lambda = 1$

3.5.5.2 Sharing Costs under Collaboration (Four-Strategy Set)

Since the equation of NP_H^* and NP_L^* remains the same in the four-strategy case as in the three-strategy case, the convex curve for the joint payoff $NP_H^* * NP_L^*$, still indicates that the ideal cost sharing under collaboration is fifty/fifty. However, if the boundaries of the collaboration cost possibilities exclude the point $n = 0.5$, the cost equilibrium when firms collaborate would depend upon the critical values of cost negotiation boundaries. As stated in 3.52 and 3.54, allowing imitation will add a new collaboration restriction for each market type. Thus, to generate the new collaboration cost equilibrium, we must combine all four collaboration restrictions and consider how to properly integrate two cost negotiation sets.

Proposition 3. If a market generates persistent dominance behaviour under (technological) competition, firms collaborate when collaboration cost for firm L satisfies:

$$n = \begin{cases} n_1, \text{if } n_1 > 0.5 \\ 0.5 \\ \min(n_2, n_5), \text{if } \min(n_2, n_5) < 0.5 \end{cases}$$

***Proposition 4*.** If a market generates action reaction behaviour under (technological) competition, firms collaborate when collaboration cost for firm L satisfies:

$$n = \begin{cases} \max(n_3, n_6), \text{if } \max(n_3, n_6) > 0.5 \\ 0.5 \\ n_4, \text{if } n_4 < 0.5 \end{cases}$$

Since the collaboration rents are higher than the imitation payoff, R_6 must be bigger than R_5. In addition the spillover index lies between 0 and 1. Thus we may prove that $n_5 < 1$, indicating that in a four-strategy persistent dominance market, the maximized collaboration cost percentage paid by L, n, must not be greater than 100%.

Prediction 17: In a four-strategy persistent dominance market, (different from the three-strategy case), the collaboration cost portion paid by the lower technology firm will never exceed 100%.

Combines the conditions on α determining the probability of collaboration in Table 3.8 and propositions 3 & 4, Table 3.9 below shows under what circumstances firms will collaborate and the cost share needed to be paid by the technology follower L in a four-strategy set. Comparing with the similar table in the three-strategy case, Table 3.9 clarifies the impact of the possibility of imitation on when firms will collaborate and how costs will be shared in equilibrium.

Table 3.9 Conditions of Collaboration Cost in a Four-Strategy Market

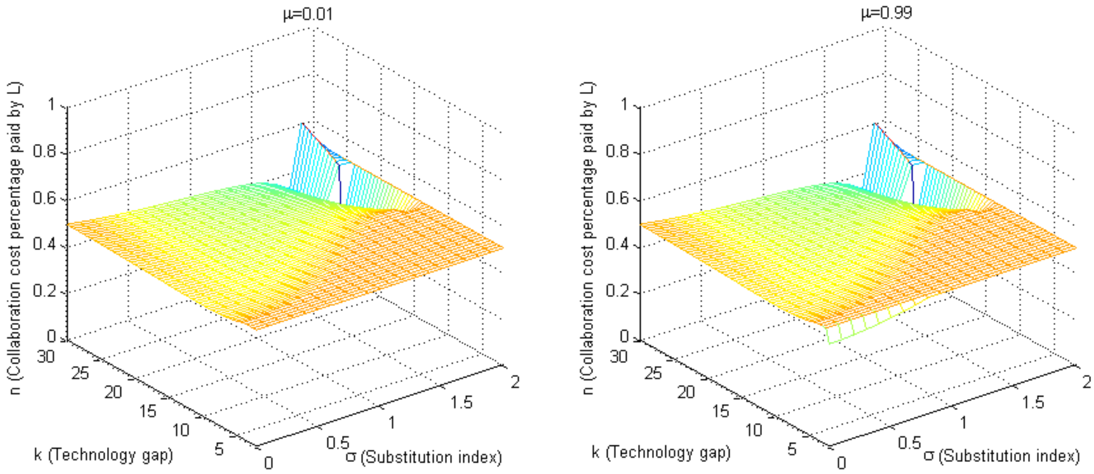
Range of α	Market Type	Range of n	Sub-range of n	n
$(-\infty, \max(\alpha_1,\alpha_2))$	$h_1 > l_1$ (KD)	No Collaboration		
$[\max(\alpha_1,\alpha_2), \min(\alpha_3,\alpha_5)]$	$h_1 > l_1$ (KD)	$(n_1,n_2)\bigcap(n_1,n_5)$	$n_1 > 0.5$	$n = n_1$
			$n_1 \le 0.5 \le n_2$	$n = 0.5$
			$\min(n_2,n_5) < 0.5$	$n = \min(n_2,n_5)$
$(\min(\alpha_3,\alpha_5),\alpha_3]$	$h_1 > l_1$ (KD)	No Collaboration		
$(\alpha_3, \max(\alpha_3,\alpha_4,\alpha_6))$	$h_1 < l_1$ (AR)	No Collaboration		
$[\max(\alpha_3,\alpha_4,\alpha_6), +\infty)$	$h_1 < l_1$ (AR)	$(n_3,n_4)\bigcap(n_6,n_4)$	$\max(n_3,n_6) > 0.5$	$n = \max(n_3,n_6)$
			$n_3 \le 0.5 \le n_4$	$n = 0.5$
			$n_4 < 0.5$	$n = n_4$

We note that the extra restriction that the imitation possibility introduces may reduce the frequency of collaboration relative to the three-strategy case. Collaboration may not occur because (i) under collaboration, the market may no longer offer positive prices, output and revenue, nor allow a reasonable range for cost sharing (ii) imitation may offer a higher net payoff rather than collaboration and (iii) room for the negotiation of collaboration cost has been reduced to zero.

As in section 3.5.4.2, we use MATLAB to merge the two ranges of n for each market type to simulate the collaboration cost percentage functions. By adding an additional loop syntax before the cost selection programme, the software allows the model to pick out fitted critical value of n to form a new upper or lower bound, which is then used in the cost selection models in the second part of the programme. As in section 3.5.4.2, the 3-D figures below demonstrate how the collaboration cost portion changes as other factors, such as the product substitution index, the technology gap, the initial technology level and the discount rate of price sensitiveness change. In addition, to reveal the impact of imitation, we show results for a spillover index of 0.01 and 0.99.

Figure 3.29, for instance, reveals that in general, regardless of the strength, imitation as an extra strategy option may not much change the collaboration cost figure. But as the spillover index increases, the collaboration cost may reduce significantly given a low value of the technology gap.

Figure 3.29 Impacts of Technology Gap and Substitution Index on Collaboration Cost in a Four-Strategy PD Market

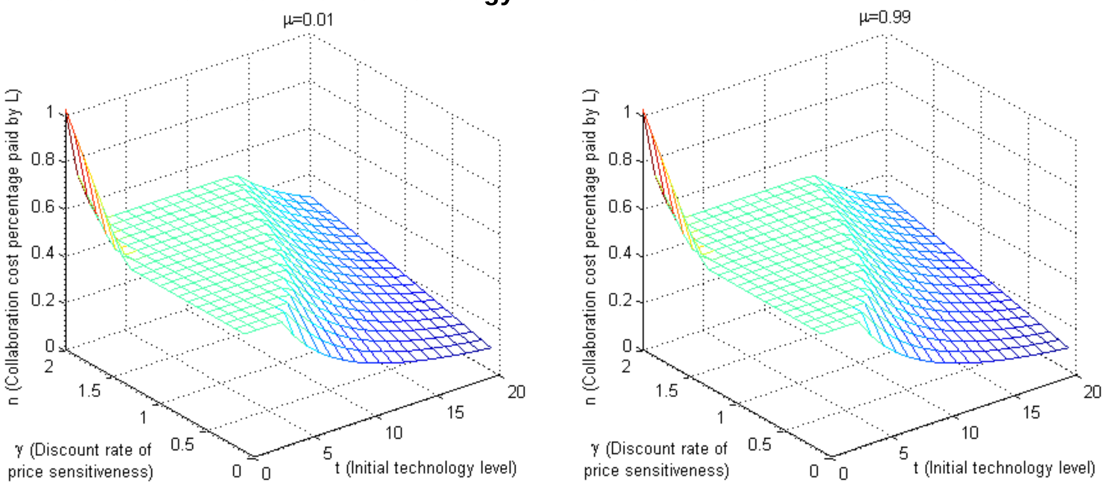


$\sigma = [0,2]; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

Similar deductions may be generated from the comparison of figures when other factors change for both persistent dominance and action reaction markets. Figure 3.30 to 3.32 illustrate that regardless of the market types and the transaction cost level, the collaboration cost proportion remains as in the three-strategy case no matter what the strength of imitation. We thus state:

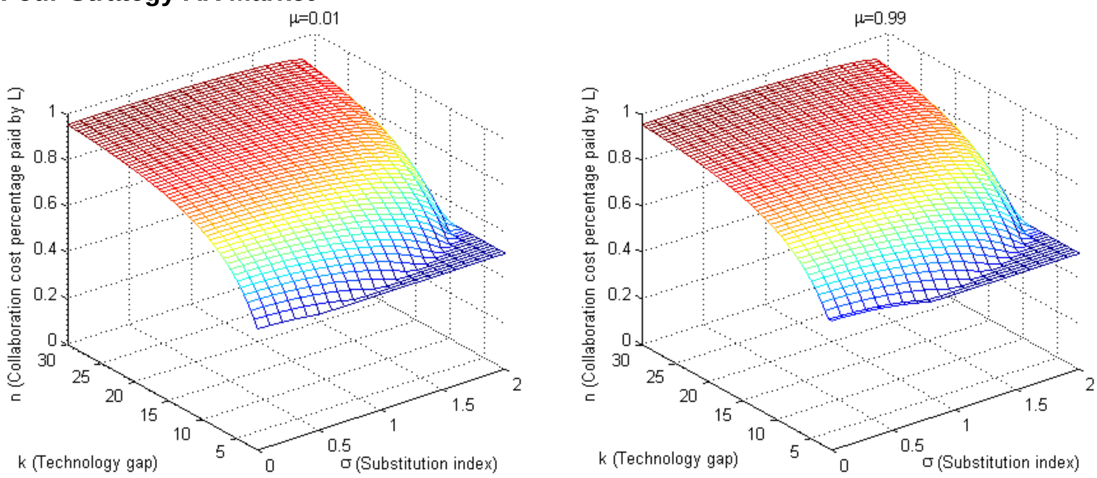
Prediction 18: There are generally no significant differences between the collaboration cost equilibrium in the four-strategy case and the three-strategy case. However imitation may induce a lower collaboration cost share for firm L if there is a small technology gap.

Figure 3.30 Impacts of Initial Technology Level and Discount Rate of Price Sensitiveness on Collaboration Cost in a Four-Strategy PD Market



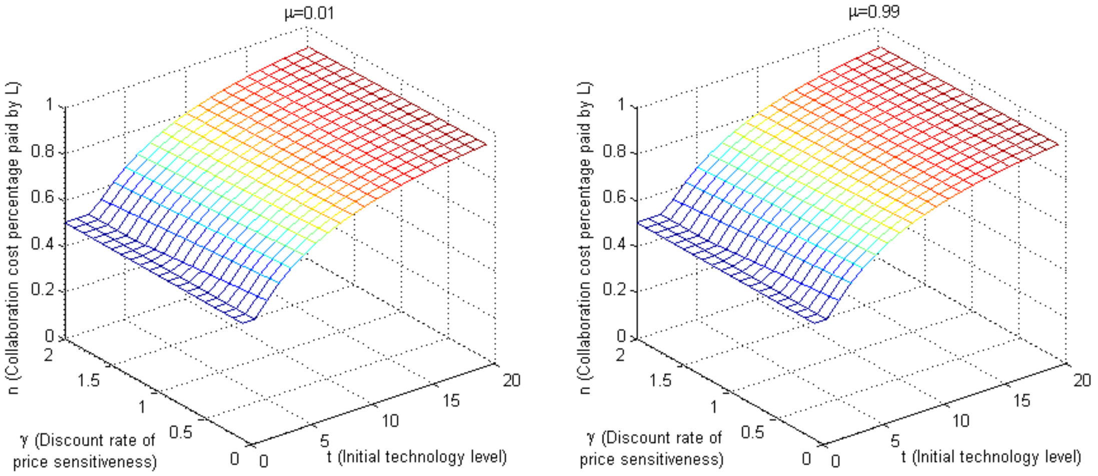
$\sigma = 0.1; k = 10; t = [0,20]; \gamma = [0.1,2]; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

Figure 3.31 Impacts of Technology Gap and Substitution Index on Collaboration Cost in a Four-Strategy AR Market



$\sigma = [0,2]; k = [2,30]; t = 10; \gamma = 1; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

Figure 3.32 Impacts of Initial Technology Level and Discount Rate of Price Sensitiveness on Collaboration Cost in a Four-Strategy AR Market



$\sigma = 0.1; k = 10; t = [0,20]; \gamma = [0.1,2]; \beta = 0.5; \lambda = 1; \alpha = 15; \theta = 10$

3.6 Conclusion

3.6.1 Contributions and Findings

The analysis in this chapter, inspired by Vickers (1986), is based on a two stage game with two players and the sequential arrival of new product technology. Compared with the original work by Vickers, three main changes have been made. One is that collaboration is considered (as well as imitation) within the firm strategy set, another is that the model concerns product innovation rather than process innovation and thirdly transaction costs linked to collaboration are included as well as R&D costs.

Each firm is allowed to produce one product variant in each time period and tries to optimise its net payoff when it encounters new technology. The strategy that suits each firm mainly depends upon the strategy incentives, which according to the theory of creative destruction, are defined by the different payoffs from pursuing a strategy and not pursuing that strategy. By assuming a strategy decision path, we compare the strategy incentives under different situations to generate a decision map for the lower technology firm. We are particular interested in the conditions and determinants of collaboration incentives, collaboration and cost sharing under collaboration.

We propose an example by employing a utility function similar to that introduced by Shaked and Sutton (1990) and Matsubayashi (2007) to find the equilibrium outputs, prices and revenues. This improved utility function contains a product substitution index and reflects the degree of market symmetry, allowing product differentiation even when firms use the same production process, thereby indicating that firms have to consider both consumer preferences and production costs when they decide whether to collaborate. In particular, we first calculate the firm's rival's optimal output level and then use backward induction to generate the best response function for each player when the market reaches equilibrium. By assuming a cost function associated with the technology level of products, a spillover index and transaction costs, it is possible to detail strategy incentives by substituting the post-strategy payoff and corresponding costs. The way the cost function is defined suggests that when firms collaborate, they need to maximize their post collaboration payoff as well as to minimize their collaboration cost proportion.

An important characteristic of our approach is that we employ MATLAB to programme both the collaboration opportunity restrictions and the modelling of collaboration cost percentages.

Our model predicts under what condition firms will collaborate and under what conditions they will not. It also predicts what the collaboration cost percentages will be if firms collaborate. All our predictions are summarised in Table 3.10. The predictions are classified into three groups. One group focuses on the probability of collaboration, one is concerned with collaboration cost, and the third group is about other issues. Note, in particular, that the predictions in the first two groups may differ according to market type (i.e. persistent dominance vs. action reaction) and strategy set (i.e. three-strategy set vs. four-strategy set).

Table 3.10 Generated Predictions

Predictions	Keynotes of each Prediction
	Predictions about the Probability of Collaboration
3	In a three-strategy persistent dominance market, the probability of collaboration generally increases with the product substitution index, the initial technology level and the discount rate of price sensitiveness, but decreases with the technology gap.
5	In a three-strategy action reaction market, the probability of collaboration generally increases with the initial technology level, but decreases with the technology gap, the product substitution index and the discount rate of price sensitiveness.
13	In a four-strategy persistent dominance market, where the transaction cost is low, adding the option of imitation would decrease the probability of collaboration when the product substitution index is high or the initial technology level is low, where firms in both situations may prefer to imitate rather than collaborate.
14	In a four-strategy persistent dominance market, where transaction cost is low, increasing the size of imitation will further decrease the collaboration opportunity when the product substitution index is high or the initial technology level is low.
15	In a four-strategy persistent dominance market, where transaction cost is high, increasing the size of imitation will neither stimulate nor decrease the collaboration opportunity.
16	In a four-strategy action reaction market, the probability of collaboration by firms does not differ from when imitation is feasible.
4	Regardless of whether there are three or four strategies, in a persistent dominance market, increasing transaction costs will stimulate collaboration until the transaction cost reaches a certain level. When transaction cost is over that level, the chance of collaboration will not be affected by further increases in transaction costs.
6	Regardless of whether there are three or four strategies, in an action reaction market, increasing transaction cost neither encourages nor diminishes the probability of collaboration.
	Predictions about Collaboration Cost
9	In a three-strategy persistent dominance market, the collaboration cost percentage paid by the lower technology firm generally increases with the discount rate of price sensitiveness, but decreases with increases in the technology gap, the product substitution index and the initial technology level. However in a market with highly similar products, the collaboration cost percentage paid by the lower technology firm increases with the product substitution index.
10	Under a three-strategy persistent dominance market structure, if firms collaborate, the firm with the lower technology level must pay. As to the percentage he pays, this depends upon the nature and market structure of both firms. However, in rare cases, the percentage could exceed 100%.
11	In a three-strategy action reaction market, the collaboration cost percentage paid by the lower technology firm generally increases with the technology gap and the initial technology level, but slightly decreases with increases in the product substitution index and the discount rate of price sensitiveness.
12	In a three-strategy action reaction market, if firms collaborate, the firm with the lower technology level must pay more than 50% of the R&D cost.
17	In a four-strategy persistent dominance market, (different from the three-strategy case), the collaboration cost portion paid by the lower technology firm will never exceed 100%.
18	There are generally no significant differences between the collaboration cost equilibrium in the four-strategy case and the three-strategy case. However imitation may induce a lower collaboration cost share for firm L if there is a small technology gap.
	Predictions about Other Issues
1	Increases in the rival's product technology level and market size or decreases in the market structure coefficient, will decrease the firm's price, output and revenue.
2	Increasing the firm's own technology level must increase its price level and revenue (which

	reflects the theory of creative destruction).
7	Increasing the value of α may cause the market structure to change from persistent dominance to action-reaction.
8	When α is small, neither firm will wish to collaborate even though they have the chance to do so. Firms will collaborate only when α is above a certain level.

The majority of these predictions are new to the literatures. To some degree at least this is because, unlike most other studies, these predictions represent a systematic strategic mapping relating to the determinants of collaboration and collaboration cost on product innovation rather than process innovation. One may note that the results also, innovatively, focus on the cost percentage paid by the low technology firm when collaboration occurs. To the best of our knowledge, this is the first model that has provided a game theoretic exploration of the decisions of firms on low technology firm's cost sharing strategy when it collaborates.

Although the initial assumptions were inspired by Vickers (1986), we focus more on product innovation and more importantly, emphasise the impact of the possibility of collaboration on the equilibrium outcomes. In Vickers model, he concluded that Bertrand competition generates a persistent dominance market, whilst Cournot competition leads to an action reaction market. In other words, competition today discourages competition in the future. Vickers therefore explores how the way that firms choose strategies can result in different market types. In our model, however, we would rather look into how firms choose strategies upon markets with different characteristics. From figure 3.4 and figure 3.7, it is clear that the advantages of our model is that we actually able to stand back from the market type and show how strategic decisions might alter as market type changes. Indeed, although we still analyse firms' optimal strategy incentives under different market types, we allow that the strategy is endogenous.

Moreover, different from Vickers (1986), we also allow the possibility of imitation so that firms have a set of four possible strategies. When a firm's exclusive IPR can be expropriated or the number of its rivals grows significantly, the firm may consider imitation as an optional strategy thus turning a three-strategy market into a four-strategy market (which is stated as prediction 13). Vickers' model does not consider such issues. By re-designing the MATLAB animation programmes, we clearly show how the extent of potential imitation impact upon the chance of collaboration and the sharing of collaboration costs (predictions 14--16). We also showed how the size of spillovers impacted on these variables.

The predictions we have generated concerning different market types and market characteristics, are not simply grouped by revealing univariate impacts on the chance of collaboration and collaboration cost sharing. This, to some extent, helps us to address some of the more controversial arguments in the literature on the relationship between collaboration (or collaboration cost) to their determinants. For instance, some people (Oye, 1986; Coleman, 1990) argue that the extent of collaboration must decrease as the number of competitors grows, whilst Cassiman e al (2009) suggests the relationship between collaboration and competition may not be negative but instead the two go hand in hand. Our prediction 13-16 explains this debate by illustrating how differing different market types and transaction cost levels matter.

Another example is how collaboration opportunity changes as transaction cost changes (see predictions 4 & 6). These two predictions discuss the particular trade-off between collaboration and transaction cost. As addressed by Williamson (1985) and Hill (1990), transaction cost is spending incurred actually to avoid opportunism being embedded in the process of collaboration. Thus increasing transaction cost must partly decrease opportunism. But on the other hand, increasing transaction cost also absorbs profit from firms' post-collaboration payoffs. The relationship between the extent of collaboration and increasing transaction cost therefore depends upon the joint effect by balancing opportunism reduction and cost saving. Some skeptics (Schroder, 2005) argue that the change in transaction cost is often associated with a change in IPR. Tighter IPR ensures a lower transaction cost, which results in a higher chance of collaboration. They thus suggest a negative relationship between the extent of collaboration and transaction costs. In our model, however, we explain this in the following way via the impact of imitation. When the spillover effect in a persistent dominance market diminishes with tightened IPR, the black curve α_5 must move to a lower level, which consequently means that collaboration opportunity decreases. This idea has been incorporated in prediction 14. It should however be noted that rather than changing transaction cost through the spillover index, 'changing transaction cost' in our model only means the effect of changing θ but with other market characteristics remaining constant. Therefore, prediction 4 & 6 do not contradict to the traditional Schroder's view but rather offer an alternative angle to observe the relationship between collaboration and transaction cost.

3.6.2 Limitations

Compared with most of literature concerned with two player games modelling competitive innovation auctions, the depth of the theoretical models which we have employed more generally explore firms' optimal strategy. We model both the collaboration incentive and collaboration. However, as with all modelling there are limitations.

1. There may be other strategy options than those which we consider. For example we allow four options which firms may choose when they encounter a superior technology in market. There may be other option such as licensing or outsourcing, which could be considered.

2. Our model excludes uncertainty. The game we analyses is a deterministic bidding game and the patent race, therefore involves no risk. However, in reality, innovation, imitation, or collaboration must all involve uncertainty. Firms try to innovate (or imitate, or collaborate), but have no guarantee of success of innovation, even if the input of R&D is extremely high. Introducing uncertainty would have complicated our modelling too much.

3. In our model, the number of players who collaborate we assume is restricted to two. But in reality the game could be a multi-player game. Firms may even form subgroups to collaborate against or with their common rivals.

4. Collaboration partner in our framework are assumed to be private firms. In reality, firms may not be privately owned and may also collaborate with other institutions, such as universities, self-funded institutions, or state owned enterprises. The issue of collaboration with these is not considered in this chapter.

This last point may be of special relevance to a study of collaboration in China where, in fact, the government may have ownership of most medium and big enterprises. But, in general we know little about the innovation patterns and the collaboration patterns in China, and there is very limited literature to which one may turn.

It is our intention in the Chapters that follow to explore new data upon the extent and the patterns of technological collaboration in China. In addition to illustrating “what” we also wish to explore “why”. Although the theory above will be useful in the latter exercise, the limitations of the theory mean that there is no simple read over from the theory to the empirics. It is our intent to use the predictions above to guide our empirical work below rather than using the empirical data below to test the theory above.

4 Datasets and Indicators

4.1 Introduction

This Chapter is primarily concerned with initial analysis of a previously unused short panel of firm level survey data in order to reveal the patterns of innovative and collaborative activity in Chinese manufacturing industry. The chapter first details data sources and the construction of statistical indicators prior to presenting the revealed patterns.

The chapter is the first of two parts that provides some empirical insight into the issue of collaboration in innovation. The previous chapter has explored theoretical issues whereas these two chapters concentrate mainly upon empirical analysis. In an ideal world it would be the case that the empirical analysis would lead on in a seamless form from the theoretical analysis with the latter providing clear guidance as to the definitions of variables, functional forms and other such matters and the former would be capable of providing measurement of variables and parameters just as necessitated by the theory.

In this case however moving from theory to empirics is not simple, particularly when issues concern, for example, the nature of the Chinese economy. It is not a simple market economy where firms are owned by private individuals or shareholders and firms may act as indicated by private incentives. The state has had and still has a much larger role to play than that. Specifically, in contrast to the assumption in the game theory chapter which only allows firms to collaborate with other firms, in China we find that firms collaborate extensively with local and national non-commercial institutions and also with overseas institutions. Similarly in the theory chapter we tended to concentrate upon product innovation rather than process innovation. This is a distinction that is difficult to maintain given the data source.

For these and other similar reasons, in this and the next chapter, rather than trying to impose the theoretical framework employed above upon a world that is different in many respects from what has been assumed in that framework and thus attempting to validate or invalidate specific predictions from the game theory chapter, we intend instead to utilise game theoretical predictions only as a guide to the exploration of the empirical data. The guidance indicates the concepts at which we wish to look and provides some suggestions as to how variables may be measured, but it is only guidance that is provided and not precision.

In section 4.2, we first discuss the nature of our firm-level datasets, including the benefits of using data from the National Bureau of Statistics of China (NBS), data collection and sample characteristics. To the best of our knowledge this is the first occasion on which data from the 'China Innovation Survey' and the 'Annual Corporate Financial Survey' has been used for such purposes and as such suggests that there is a definite contribution to knowledge being made.

Section 4.3 addresses the measurement of variables and indicators to be used in the empirical analysis in this and the next chapter. It is here that we make the link between the theory above and the realities of the data. Our discussion leads us to define three "dependent" variables and five main explanatory variables, 'R&D' (R&D), 'patent' (PAT), 'education' (EDUC), 'technology level' (TL), and 'technology gap' (TG) as well as other relevant control variables, such as 'spillover effect' (SE), 'perceived price' (PP), 'district'

(DIS), 'registration' (REG) and transaction cost which is respectively represented by 'market concentration' (MCON), 'operational personnel ratio' (OPR) and 'complementary assets' (CAST). Section 4.4 provides an overview of the data as well as breakdowns by time and industry, and correlations among the variables. The final section summarises the findings and provides markers re the content of the next Chapter.

4.2 Nature of the Datasets

The data employed in our empirical work is derived from the China Innovation Survey and the Annual Corporate Financial Survey undertaken by the National Bureau of Statistics of China (NBS), which is the only official authority offering data gathered by the Chinese government.

The advantages of using NBS data are that: (i) Cooperating with NBS is efficient in terms of time demands and expense. A separate data gathering exercise would be out of the question. (ii) Although currently, in China, a small number of institutions, funded by various universities (such as Peking University, Tsing Hua University, and Nan Kai University), gather firm level information across industries, the NBS data encompasses more firms and more indicators than other sources. In fact for some firms with specific ownership patterns, such as state enterprises with a military background, it is difficult to obtain data and the only agreed authority to collect data from all firms in China is NBS. (iii) NBS applies a universal standard of statistical definition and measurement of classification for each term and each firm which may differ from that in other surveys. For example, the term 'firm' in the China Innovation Survey and Annual Corporate Financial Survey, was defined as organisations with annual revenue at or over fifty million yuan (about 5 million pounds) – so called Large and Medium sized Enterprises[3] - but in other databases the definition of a firm may differ across source and time. The common NBS definitions are reinforced in that, for each firm, selected staff are obliged to attend a regular training (workshop) offered by NBS in order to fully understand statistical definitions and the way of filling in survey forms. This significantly reduces the possibilities of errors in the data gathering process. Using surveys organised by central government thus provides the best chance of obtaining valid and truthful data.

The pyramid like structure of NBS contains a large number of downstream local statistics departments, which are in charge of local data gathering and usage. I cooperated with the Nan Chang Statistics Department. As such local departments are only able to provide data on local firms this means that our empirical analysis encompasses only firms located in Nan Chang city. We chose Nan Chang for two reasons. First they were willing to collaborate with our study. Second, Nan Chang is the capital of Jiang Xi province, located in central China, and well represents the middle income level in China. It is one of the faster growing cities in China, at a rate in excess of 15% in five continuous years from 2003[4], which is significantly higher than the national average growth rate. Industry structure in 2005 (2007) was 7.2% (5.8%) primary industry (Agriculture), 52.8% (55.1%) secondary industry (Industry), and 40% (39.1%) tertiary industry (Service and Others), indicating

[3] Indicating, of course, that all conclusions obtained from our analysis should be read as only relating to Large and Medium sized Enterprises

4 To be more precise, the five year GDP growth rates excess from 2003 are, 15.5%, 16.5%, 16.8%, 17.5, and 17.4%, respectively.

significant growth in the secondary sector. In particular most of the GDP growth at Nan Chang was contributed by manufacturing industry, including high-tech firms (http://www.jxgdw.com, 2008). More information about industrial sector definitions and classifications will be detailed in the following sections.

The data we are employing is firm level data covering Manufacturing in Nan Chang from 2005 to 2007. The reason we chose manufacturing as our test bed is because Manufacturing is commonly agreed to be an engine of growth (Cornwall, 1977; Fagerberg & Verspagen, 2002) and is a sector where technological competition is probably more intense than in other sectors of the economy. As our concern is the circumstances that cause firms to collaborate and innovate, this is probably better than employing data from other sectors with less technological competition.

One problem with accessing and using firm level data in China is that, according to the article 15 of Chapter III 'The Administration and Publication of Statistical Data' in the Statistics Law of the People's Republic of China:

> *'Statistical data pertaining to State secrets must be kept confidential. Single item investigation data concerning any individual or his / her family shall not be divulged without the consent of the said person. Statistics institutions and statisticians shall have the obligation to maintain commercial secrets of the units and individuals under their statistical investigation, which they have come to know in the process.'*

Such restrictions have limited the extent to which the data that are employed here have been used in the past. Relative to studies based upon data in other countries there are very few papers that address micro level innovation strategies in China. Even in such studies that do exist, most focus on province (state) level data rather than firm level data. In the work reported upon here we have been able to overcome the problem of maintaining confidentiality and as a result this work merits recognition as the first to use firm level data to investigate firms' innovation and collaboration strategies in China (and in fact in any mid-income level developing country).

Given the confidential nature of the data and the limit of the Statistics Law of the People's Republic of China, the original survey data was modified by the Nan Chang Statistics Department to first erase sensitive firm level information such as firm name, firm code, firm contact, and firm precise geographical location. Then, for identification, each firm was marked by a unique reference number. This number is not only very important when we combine the information from four different forms in the two surveys, but it also, in particular, is necessary to create the data panel across years. However, all other information which cannot be easily used to allocate firm identity, such as, date of foundation, firms' industry code, and the amount of R&D spending, etc. were made completely available. This has meant that we have available a rich source of firm level information thereby enhancing our results. Initially we were not allowed to immediately access the data from the Nan Chang Statistics Department. Instead, we went twice to their local office to undertake our analysis. Eventually however we were granted full access to their online database under staff surveillance.

The data employed here comes from the annual report database (as opposed to the quarterly and half year surveys which are also undertaken). The longer time window covered by an annual report is seen as advantageous. The data we use covers the years from 2005 to 2007. Prior to 2005 different data collection forms with different emphases and questions were employed by NBS. In fact, before 2005, most indicators relating to innovation activity were generated by the Economics Survey and the Manufacture Survey respectively, which mainly focused on output value, cost saving or individual profit rather than innovation activity. Even though firms were asked 'Did the firm innovate this year?' or 'How many innovations did the firm adopt this year', there was little further detail on matters in which we are interested; for example 'what kind of innovation' was not asked in the earlier survey. It is thus not possible to take our data back before 2005.

In addition, in China, firms' innovation environments significantly improved after 2005. Many high-tech firms were assembled by local governments to generate cluster effects. In particular, from 2003, the Nan Chang government introduced an innovation scheme named 'Two-Four-Five' project. In this project, by the end of 2010, the innovation related cluster would include: two-areas ('A Technical Economic Development Area' and 'A High-tech Industry Development Area'; four-parks, 'A Local industrial Park', 'An Affiliated Facilities Industrial Park', 'A Returnee Innovation Park' and 'A University Innovation Park'; and five bases, 'A High-tech Industry Base', 'An Industrial Gradient Transfer Industry Base', 'A Big Enterprises' Affiliated Facilities Industry Base', 'A Green Environmental Protection Food Industry Base' and 'A Characteristic Products Industry Base'[5]. To achieve this long term goal, Nan Chang provided a special manufacturing fund with 40 million RMB in 2004 and invested 10 million RMB from 2005 to reinforce technology-cluster[6].

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[5] The policies are stated in the internal government document, 'Decisions to Speed up Building Modern Manufacturing', Hong [2003]22, where Hong is the city abbreviation of Nan Chang, whilst [2003]22 represents this document as the 22nd internal document produced in year 2003. Please note, as unpublished materials are normally excluded from reference lists or bibliographies, we address cited internal government document in footnotes. Policy resources, therefore, also follow this rule.

[6] 'Policy Details about Manufacturing Development ', Hong [2004]30

Also, to speed up the development of high-tech industry, benefits were introduced to reward firms or individuals that frequently innovated, including tax deductions, loan subsidized interest, resource supply priority (water, electricity, petrol), and individual innovation contribution prizes. To be more precise, any innovation project with investment whose amount is below 200 million RMB, could benefit from a construction tax deduction of up to 80%, whilst investment on innovation projects above 200 million RMB, could obtain a construction tax exception. In particular, for large or major innovation projects, firms could receive loan subsidised interest up to 1 million RMB for a single project[7]. Besides, a local science and technology competition is held annually. The winner of the competition will be awarded up to 100 thousand RMB individual bonuses plus 400 thousand RMB research funding[8].

Moreover, other exclusive policies have been generally introduced for attracting highly skilled and highly talented workers, including experienced engineers and prestigious researchers. The policy ranges widely, from salary bonuses to housing subsidies[9]. Even though such policies can not directly influence innovation size and frequency in Nan Chang, they all at least to some extent, still increase innovation capability in the future.

Such policies will have significantly impacted upon the innovation environment in Nan Chang. Allowing for time lags in the impact of policy this suggests that, although our data does not allow us to go back before the year of

[7] 'Management of Special Fund for Nan Chang's High-tech Industry', Hong [2003]27

[8] 'Nan Chang Science and Technology Awards Rules', Hong [2006]114

[9] 'Housing Benefits for Attracting Highly Skilled People', [2003]31; and 'Measures for Introducing National Highly Talented People', [2003]41

2005, any attempts to do so might well be self-defeating because of the different environment in those earlier years.

Our data ends in 2007 as this was the latest year for which we could get access to the database from the local statistics department. According to the Statistics Law of the People's Republic of China, data must be carefully assessed before being formally released to the public. The release order firstly comes from the central government, to provincial government, then to local government. That is to say, the public may first read national statistics from the yearly statistics book issued by NBS, then provincial statistics, and finally local city statistics. This whole procedure may take more than several years which is why panel data later than 2007 is not available.

The two surveys we are using, the China Innovation Survey and Annual Corporate Financial Survey, were conducted independently and by different groups within NBS. This collection method reinforces efficiency and increases the flexibility and veracity of data collection but the required linking of two surveys has increased our processing time. There is some redundancy in having two data sets, and we have also found some inconsistencies in the data collected in the two surveys but we will explain more of that below.

4.2.1 China Innovation Survey

Our data from the China Innovation Survey relates to major innovations in Large and Medium sized Enterprises in Nan Chang. The database covers 33 major industries, including High-tech industries, in both manufacturing and services, with annual & monthly panel data on a rich array of information on firms' registered details, industrial development status, employment, main economic indicators, gross output value, and product sales revenue. Details about technology change such as R&D expenditure, technology change funding resource, and number of patents, are also included.

The survey consists of three NBS designed forms in total: the innovation project form (Form B107-1); the innovation activity form (Form B107-2); and the corporate details form (Form 601), respectively. An English translation of each of these forms is reproduced as an Appendix to this Chapter. Every firm with annual revenue over 50 million RMB is under an obligation to fill in this set of three forms. The responses thus cover the whole population as defined by the definition of a firm.

The first form, the innovation project form, contains information on major innovation projects whose annual value is at or bigger than 100 thousand RMB. Apart from erased confidential data, such as firm code, firm name, director of project and contacts, the form includes data upon the project size, innovation nature, innovation patterns, innovation usage, innovation target, the starting and finishing date of projects, the number of people involved in projects (sorted by educational background), the number of working hours involved and internal project expenses in the reporting year.

The number of projects normally indicates the size of major innovation activities in the firm. The higher the number of projects is, the more major innovation is the firm involved with in the year. As shown in the appendix designed by the NBS, universal regulations, innovation nature, innovation pattern, innovation usage and innovation target are all classified with a subcode. A firm which receives this form, only needs to match the proper terms into the category classification and simply fills the corresponding subcode into the form. The third column, ‘Details’, in each category classification gives people more explanation to help them allocate their firms' innovation type. For example, in the regulations for classifying innovation nature, the details for National Project (subcode 1), are 'Including 863 projects, Xinghuo projects, Pandeng projects', which clearly defines the range of 'National Project'. Similarly, the survey classifies innovation by categories, which allows us to distinguish collaborative and non-collaborative projects using the pattern code. This information makes it possible to analyse the link between innovation and collaboration.

The second form, the innovation activity form, gathers detailed information on overall innovation activity, including information on people involved in innovation, funding collection (source) and expenditure, innovation output and others. It should be noted that some of the indicators overlap with the first form, but are in fact subtly different. For instance, 'the internal expenditure' (No.15) in the innovation activity form measures all the internal expenses relating to technology change occurred during that year whereas 'the internal project expense' (No.11) in the innovation project form, B107-1, only covers the amount of spending for that one project. It is the same with the indicators of 'No. of people involved in innovation activity (01)', 'people with engineering qualification (05)', and 'people without engineering qualification but with higher degree (06)' in the innovation activity form.

Thus, the second form is more focused on firms' characteristics rather than single innovation projects. This is because firms involved in many innovation projects sometimes may not easily distinguish expenditure etc, by projects. For example, some researchers may be involved in more than two innovation projects. But when we count the 'number of people involved in innovation project', simply adding across indicator 7 in the innovation project form may lead to double counting. Another possibility is that some innovation efforts produce more than one outcome. For example, knowledge accumulated from one project may increase the firms' absorptive capacity on other innovation projects. If that happens, the spillover effect of 'Expenditure on improving existing technology' (indicator 42 in the innovation activity form) may significantly influence the firms' ability to adopt or adapt the innovations from other players. Either ignoring such spillover effect or simply adding up each project's 'Expenditure on improving existing technology' in such cases could cause overestimation or serious error. To overcome this problem we try to measure such factors at the firm level rather than the project level.

The innovation activity form also has the advantage that, as we noted, the innovation project form covers only projects with an annual value bigger than 100 thousand RMB. However, for most small firms or firms with a limited innovation budget, this may be too high to meet. If the number of such small projects is large in proportion to the total then omitting them could cause serious bias. To overcome this problem, the innovation activity form (25) provides information on the total 'number of innovation projects' without any value limit. Obviously, as the 'number of innovation projects' includes those above the value limit, this term must not be smaller than the biggest value of project number in the innovation project form.

Neither the innovation project form alone nor the innovation activity form alone can fully represent firms' innovation activity. The first emphasises the nature and the type of major innovation, whilst the latter generally describes the characteristics of the firm itself and overall innovations. We have thus used both forms to construct our data set. In the empirical studies, we mainly utilise the innovation activity form to provide data on independent variables but employ the innovation project form to generate data upon dependent variables.

The third and last form, the corporate details form, introduces firms' registration information, such as industry code, date founded, place of registration, registration type, organisation type, as well as other variables. The data thus collected, being largely free of details on innovation, may be used to provide information upon control variables that may affect firm behavior and for which correction is required in the empirical work. One critical piece of information that can be obtained from this form is the industry code for the firm. Since the innovation frequency and innovation behavior may vary from industry to industry, allowing for the industry in which the firm is located is crucial.

As an OECD country, in China the industrial classification largely follows 'the International Standard Industrial Classification of All Economic Activities' (ISIC) Rev 3.1 as defined by the United Nations Statistics Division (http://unstats.un.org/). However, to better fit the Chinese situation, some modifications have been made with the order of the industry code altered by NBS and a few industry classifications modified. Each industry code contains four digits in total. The first two digits represent the major industrial sector whilst the other two digits define the firms' major products (service). In ISIC Rev 3.1, there are 16 different major industrial sectors defined. These are:

- A – Agriculture. hunting and forestry
- B - Fishing
- C - Mining and quarrying
- D - Manufacturing
- E - Electricity, gas and water supply
- F - Construction

- G - Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
- H - Hotels and restaurants
- I - Transport, storage and communications
- J - Financial intermediation
- K - Real estate, renting and business activities
- L - Public administration and defence; compulsory social security
- M - Education
- N - Health and social work
- O - Other community, social and personal service activities
- P - Activities of private households as employers and undifferentiated production activities of private households
- Q - Extraterritorial organisations and bodies

However, the NBS Chinese industry definitions combine section D 'Manufacturing', section E 'Electricity, gas and water supply' and part of section C 'Mining and quarrying' jointly labeling these as 'Manufacturing'. To be more precise, 'Mining of coal and lignite; extraction of peat' and 'Mining of non-ferrous metal ores', both of which are classified into section C in ISIC Rev 3.1, have been added into Chinese 'Manufacturing' as industry 32, and 33, whilst 'Electricity supply', 'Gas supply' and 'Water supply', all of which are classified to section E, are in China coded as industry 44, 45, and 46, respectively. In addition, the NBS counts 'Manufacture of rubber and plastics products' (code 25 in ISIC Rev3.1) as two separate industries instead of one, 'Manufacture of rubber products' (industry 29) and 'Manufacture of plastics products' (industry 30). In addition, 'Manufacture of man-made fibres' has been removed from 'Manufacture of chemicals and chemical products' (code 24 in ISIC Rev3.1) and is listed as a new independent industry. Last but not least, in the manufacturing defined by NBS, industry 12 and 38 are empty.

The industry classification (GB/T 4754—2002) currently used by NBS has been employed in data collection since 2003 (http://www.sts.org.cn, 2002) with the number of major sectors, as the following list shows, increased from 16 to

20. In particular, sector A, called primary industry, mainly represents agriculture, and sector B to E, as secondary industry, measures industry, including manufacturing, whilst the rest of the sectors, referred to as tertiary industry, are normally recognised as service sectors.

- A – Agriculture, fishing, hunting and forestry
- B- Mining and quarrying
- C - Manufacturing
- D - Electricity, gas and water supply
- E – Construction
- F– Transport, storage and communications
- G –Computer service and software
- H - Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
- I - Hotels and restaurants
- J - Financial intermediation
- K - Real estate, renting and business activities
- L –Business rental service
- M –Science research and technical support service
- N - Public administration and defence; compulsory social security
- O– Residential service and others
- P - Education
- Q - Health and social work
- R – Culture, sports and entertainment service
- S – Public management and organisations
- T - Extraterritorial organisations and bodies

Our data relates solely to firms that are considered to be part of the manufacturing sector as defined by the Chinese industrial classification. The finer industrial classification of the firms in that sector is then made according to the classification detailed in section 3 of the Appendix to this chapter. Although we had thought to separate out high-tech firms from other firms, the definition of high-tech firms in the data is a problem. In 2002 (www.sts.org.cn, 2003), the NBS released a set of definitions for high-tech firms encompassing a list of selected four digits industry codes, which is compatible with OECD's classification of high-technology industries. Apparently, only a few sub industries in each major industry were to be recognised as high- tech industry. For example suppose the industry code 37XX represents the ‘Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment’ industry while the industry code 3762 is the ‘Aircraft and Spacecraft’ industry which is recognised as one of the high-tech industries by NBS, then apart from the industry with code 3762, all other firms in the ‘Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment’ industry, 37XX, could only be counted as normal, non-hightech, manufacturing industry. This we have considered to be too restrictive. Therefore, for the sake of simplicity, we ignore the high-tech industry classification.

4.2.2 Annual Corporate Financial Survey

This survey was not dispatched and collected by the Society & Technology Group but by the Manufacturing Group, which generally is responsible for the calculation of statistics upon economic growth and calculating local GDP. Since the deadline for the Annual Corporate Financial Survey is normally set at the beginning of the following year, a date later than the China Innovation Survey, the data collection always produces a better result. For instance, there are some missing values for ‘annual revenue of major products (service)’ and ‘value of assets’ (indicator 18) on the corporate details form. But in the Annual Corporate Financial Survey, both indicators are also included and there are no missing values. Therefore, to provide a better data set we substitute for the value of these two indicators in the corporate details form and ‘number of people involved in innovation activity’, (indicator 01 in the innovation activity form), by the equivalent data from annual corporate financial survey.

The other point we should note about this survey is that the value of profit does not equal the difference between ‘revenue of major products (service)' (code 124) and 'cost of major products (service)' (code 125). This is because: the gap between 'revenue of major products (service)' (code 124) and 'cost of major products (service)' (code 125) may not be exactly the same as the difference between the revenue from ALL products (service) and the cost of ALL products (service). When calculating firms' profit, other expenses, such as operating expenditure, administration cost, and fiscal expense should be taken into account as well, which would significantly diminishes profit. However we do not have the data available that would allow this.

Compared with the China Innovation Survey, the Annual Corporate Financial Survey provides extra data upon the value of stock (code 002) including final goods (003). These, to some extent, indicate the popularity of the firms' products on the market, in that, ceteris paribus, the less popular is the product the larger will be the value of unsold stock. In addition the value of stock minus the value of stocked final goods provides an indicator of the value of the stock of intermediate goods. We will make use of such data as spillover indicators in the following section.

4.3 Indicators

In Chapter 3 above we have used game theoretic methods to produce a large number of predictions as to the determinants of whether firms collaborate and, if they do, how collaborations costs will be shared. The predictions are summarised in Table 3.10. These are of course some of the matters that we are here approaching empirically. However, moving from these theoretical predictions to the empirical work is fraught with difficulties. This is for two main reasons.

First the theoretical approach developed in the previous chapter does not neatly transfer to the real world context. Three examples of this problem are: (i) in the game theory model, collaboration meant collaboration between competing rival firms in a given market firm but the data for the Chinese region studied reveals that most collaboration activities have been between firms and local government; (ii) in the theory firms are assumed to be competing rivals, in reality, collaboration may be with firms that are upstream or downstream of each other; and (iii) the game theoretic model concentrates upon product innovation whereas in fact firms undertake both product and process innovation.

Secondly, although the theoretical chapter provides a number of predictions these are both limited and in many cases involve parameters and constructs that are either impossible to observe or difficult to measure. Thus for example in Table 3.10 key issues concern whether (i) the market is an action reaction or a persistent dominance market and (ii) whether firms perceive the world to offer three or four strategies. We are unable to observe these factors. One might also note that the models provide no predictions at all as to what are the determining factors of whether the firms introduce new products or processes (through either innovation of collaboration) but rather concentrate upon whether any new products will be generated by collaborative activity or not. Having said this however we should note that the theory does suggest that there are certain variables that are relevant to the issues under discussion and as such may merit some empirical attention. In particular we note that technology level, technology gap, spillover effects, perceived price and complementary assets, play important roles in the theory. Reflecting this in our empirical work indicates that we are using the theory as a guide to analysis of the data rather than using the data as a test bed of the theory.

In order to proceed we argue that there are three main issues in which we are interested: do firms innovate; if they do innovate do they self-innovate or collaborate; and if they collaborate how the costs of collaboration are shared. These concerns lead us to the three dependent variables in our empirical analysis which we label, not surprisingly as Innovation, Collaboration and Cost Percentage. In the next subsection we will discuss their definitions and measurement.

4.3.1 Dependent Variables

Because in the China Innovation Survey questions re collaboration in innovation are parts of questions relating to innovation we start by looking at innovation activity per se.

Innovation, INNO (i ,t):

In Form B107-1, category classification, section 2, eight types of innovation activities are included. Activity pattern subcode 6, 'innovation by self-research department', is the indicator which is most commonly used in economic models as indicating whether a firm is undertaking innovative activity. However, firms may also be innovative because they are collaborating with others on innovation. Form B107-1 considers the following collaborative activities which are also different types of innovation

'Collaboration with abroad institutions';
'Collaboration with national universities';
'Collaboration with national independent institutions';
'Collaboration with registered foreign investments';
'Collaboration with registered other investments';
'Collaboration with local government';

‘Others’

We follow this reasoning and define a firm as innovative if it is undertaking any of these collaborative activities or reports ‘innovation by self-research department’. Thus, compared to the use of the term ‘innovation’ in the game theory chapter, which only covered self-innovation, the definition of innovation we are using in the empirical analysis has a broader meaning, including both self-innovation and collaboration, perhaps thereby tending more towards a more general sense of technological change.

We employ a binary variable, INNO (i,t), to represent whether firm i innovated in year t. Therefore, if the firm carried out innovation INNO (i,t),would be measured as 1 and otherwise as 0. These data may then be used to classify firms as innovative or non-innovative.

Collaboration, COLL (i, t):

In contrast to the assumptions of the game theory model, in China, many Large and Medium sized enterprises or institutions are either owned by government or have government support. Thus instead of restricting ourselves to only collaboration between firms as considered in the game theory chapter, a full picture of collaborative activity requires that we also consider collaboration with non-market institutions and national and local government.

Once again Form B107-1, part 2, provides information upon whether firms have collaborated. Of the classes listed all but subcode 6, ‘innovation by self-research department’, could be considered to be collaboration. We consequently define a binary variable COLL, that it reflects whether the firm has collaborated or not, according to whether the firm makes a positive response to any part 2 subcode other than subcode 6.

Cost percentage, CP (i,t)

The game theoretic analysis above provides for the first time some insight into how the firm with lower technology will share in collaboration costs. However, it is difficult from the data to classify a firm as a technology leader or follower and as such for empirical purposes the theoretical predictions are of little use. In the empirics therefore we concentrate upon how collaboration cost varies with other variables. This approach will give us a general picture of collaboration cost changes and contribute to a wider literature rather than just discussing the lower technology firms' collaboration cost sharing strategies. As collaboration, the empirical analysis of cost sharing will differ from a direct carry over from the game theory chapter.

Form B107-2, code 22 provides information upon 'External expenditure by collaboration' which represents the firm's collaboration cost. Making use of the industry classification (Form 601, code I), we may also explore the average collaboration cost in different industries. Then we may investigate the cost percentage variable CP (i,t), by taking the ratio of a firm's collaboration cost to the sum of industry average collaboration cost and the firm's collaboration cost. The value of this variable, CP, should be in the range between 0 and 1. The higher this value is, the higher cost percentage the firm bears when it collaborates.

4.3.2 Independent Variables

In the absence of clear theoretical guidance (although not completely ignoring our theory) we need to take a more eclectic and less precise view at what factors determine innovation collaboration and cost shares. The independent variables which we explore as determinants of innovation, collaboration and cost allocation strategies, mainly derive from three aspects of the firm - innovative ability, absorptive capacity (Castellacci, 2008) and catching up capacity (Blalock & Gertler, 2009).

We choose these three factors because they are all trigger factors in technological growth. The former two focus more on conditions within the firm, whilst the last pays more attention to exogenous conditions. One approach (Castellacci, 2008) suggests that the latter two factors determine the "club" to which a firm may belong. High innovative ability and absorptive capacity results in being amber of the advanced club; low innovative ability but high absorptive capacity leads firms to be in the followers club; while poor innovative ability and absorptive capacity results in the firm being in the marginalized club.

On the other hand, according to the Schumpeterian concept, as catching up ability relates to players' technological positions in markets and technology diffusion, this may also consequently influence firms' decision on technology changes (Nelson & Phelps, 1966; Blalock & Gertler, 2009).

These three factors are multi-dimensional concepts and as such measured by a number of different variables. In the following we detail what these variables might be and how they are to be measured. As we do so we also discuss why/how the variables may impact on the dependent variables of interest. Most of independent variables illustrated below are inherent from relevant concepts in existing literatures, such as R&D, PAT, EDUC, whilst others, such as TL and TG, are inspired by our game theory model. However, since very little empirical work addresses the collaboration cost sharing problem, there is little guide as to how to proceed empirically. So we use the same variables to look at the determinants of the collaboration cost sharing in the following chapter.

The first aspect, innovative ability is measured by looking at two interrelated concepts, innovation input and innovation output. The innovation input is normally measured by R&D, whilst the innovation output is measured by the number of patents applied for or owned. Although high correlation may be observed between R&D and patents (Kleinknecht, 1996), to explore whether firms' collaborative strategies vary with innovation input or innovation output, we employ both of them as indicators to investigate the impact of innovation ability on collaboration and collaboration cost, unless this causes severe autocorrelation. For innovation, however, since our measure of innovation indicates that any firm (or innovation project) must involve some R&D input, R&D may not truly be an independent variable. Therefore in modelling whether firms innovate, we explore the role of innovative ability by using innovation output only.

R&D, R&D (i, t):

R&D is normally regarded as the main measure of innovation input, and in some literatures is quite closely linked with the amount of innovation (collaboration) (Tomiura, 2009). Aghion etc (2001) suggest a negative correlation between firm innovation and its R&D spending in the previous periods. However most studies indicate that R&D normally increases innovation (Davidson and Segerstrom, 1998) and even firm size (Kleinknecht, 1996). As suggested by Fagerberg (1987) and Castellacci (2008), compared with other indicators, R&D normally has wider coverage, we therefore define R&D as representing innovation ability from the innovation input aspect. To calculated R&D of firm i in year t, we take the logarithm of the sum of 'R&D expenditure' (Form B107-2, code 20) and 'expenditure on new products' (Form B107-2, code 21).

Patent, PAT (i, t)

PAT, as the abbreviation of the variable representing patenting activity, represents the innovative ability from the innovation output aspect. Differently from R&D as an innovation input, innovation output is sometimes underestimated when people measure innovations. As the 'pure' technology efforts between technology leader and technology follower are often represented by patents, Fagerberg & Verspagen (2002) claimed that innovation measured by patenting activity must become more and more important. To look into the 'Innovation Activity Output' section in the form B107-2, we define the measurement of innovation output, PAT, by the firm's stock of patents as measured by the sum of 'Number of applied patents' (code 39) and 'Number of owned patents' (code 41).

The second aspect of independent variables we are looking into is absorptive capacity, which indicates determinants related to the firms' ability to absorb innovations. Cohen and Levinthal (1990) consider that absorptive capacity may refer to *'ability to recognize the value of new information, assimilate it, and apply it to commercial ends'.* It not only affects the process of technology diffusion and technology transformation, but also, more importantly, it influences the success of technological change (Fagerberg, 1987). Most literatures suggest this variable closely relates to the educational background of human capital, including literacy rate, secondary schooling and higher education (Castellacci, 2008; Blalock & Gertler, 2009). That is because firms need skilled personnel to successfully adopt new technology (Blalock & Gertler, 2009). On the other hand, dramatically increasing R&D budgets, to some extent, may also increase the absorptive capacity and reduce the technology gap between technology follower and frontier. Klein and Lim (1997) however, emphasise that, compared with the importance of researchers, the positive impact from R&D becomes quite limited. By analysing independent technology development in Japan and Korea from 1974 to 1988, they conclude that the stimulation on achieving gap reduction from increasing researchers is relatively larger than from R&D growth. We therefore measure firms' absorptive capacity by firm level human capital, as follows.

Education, EDUC (i,t)

We employ data on 'People with engineering qualification' (Form B107-2, code 05) and 'People without engineering qualification but with higher degree' (Form B107-2, code 06). Together they represent the number of people with a higher educational background. Also, we employ 'People involved in innovation activity' (Form B107-2, code 01) as people who are involved in R&D activity. The variable, EDUC is the ratio of people who are involved in R&D activity with a qualification or higher degree relative to the total number of personnel employed in innovative activity. Since previous research (Ke & Luger, 1996) suggest that R&D staff with higher educational background may help to increase firms' absorptive capacity, we claim that when firms launch technology change strategies (innovation, imitation or collaboration), the higher ratio EDUC, the higher possibility of success would be.

The last aspect of explanatory variables influencing strategy decisions is the capacity to catch up, measuring the possibility and ability that firms catch up with the technological frontier. Some people suggest that catching up capacity may be counted as part of firms' absorptive capacity, because it measures technological infrastructures (Castellacci, 2008). But others argue that to catch up with technological leader, any factors influencing firms' rival's position must be as important as their own technology position. This indicates that any other determinants including endogenous characteristics of firms themselves or exogenous characteristics of the market may both affect players' catching up capacity. Instead of being part of absorptive capacity, we therefore prefer to discuss catching up capacity separately. To be more precise, to measure catching up capacity, we employ two variables technology level (TL) and technology gap (TG).

Technology level, TL (i, t)

The first variable representing catching up capacity is defined as *'the ability to use technological knowledge efficiently and to the extent to which* technological knowledge is accumulated, invested in, produced and innovated' (Ryu & Byeon, 2011). This also describes the technology level of firms at the opening of any competitive competition. Indeed, although there are some recent empirical studies discussing how firms' technological catching up capacity varies upon initial technology conditions (Castellacci, 2008; Canova, 2004). There is no simple indicator of this variable. Neoclassical theory believes the technology development is closely related with labour and capital. Ryu and Byeon (2011) evaluated the technology level using a technology growth curve. But others, Soete (1981), account for the impact of this variable as a partial effect of innovative ability rather than classifying it as a separate determinant. Fagerberg (1987) who tested the technology gap approach by employing data on 25 countries from 1960-1983, suggested use R&D or patent statistics to measure technology level. By adopting factor analysis, Klein and Lim (1997) classified eight different means of measuring technology level as developed by Sharif and Haq (1980). They are

'Real per capita GDP';
'The ratio of R&D expenditures to GDP';
'R&D expenditures per researcher';
'The number of researchers per 10,000 workers';
'The value added by the industry';
'The volume of technology trade of the industry';
'The number of patents registered for the industry';
'The ration of R&D expenditures to total sales of the industry', respectively

However, as the old technology growth curve might be constantly replaced by new technology, the methodology employed by Ryu and Byeon (2011) is not acceptable. Also, since the figure of firm level GDP, technology trade (sum of technology imports and exports), value added and total sales are not feasible in our dataset, we may only have to consider the other possibilities. We therefore decide to use the index of 'R&D expenditures per researcher' to measure the technology level variable. To do this, the 'R&D expenditures' (Form

B107-2, code 20) and ‘people involved in R&D’ (Form B107-2, code 07) are employed respectively.

Similar to R&D, since the measure of TL contains R&D, it may not be a true independent regressor for innovation. We thus exclude both R&D and TL when we estimate the determinants of innovation equation.

Technology gap, TG (i, t):

The technology gap is another important but complex indicator of the firms’ technological position and measures the technology level of the firm compared to that of its rivals. On one hand, a larger technology gap may stimulate the technology followers’ desire to replace their current technology (Verspagen, 1991). Generally, a smaller technology gap is not enough to push firms to launch innovation because firms may already pick ‘the low-hanging fruit’ technologies which are cost efficient (Blaclock & Gertler, 2009). On the other hand, firms with a larger technology gap may lack the ability to apply new technology from the technological leader. Being too far away from the leader could significantly reduce the possibility of catching up. In Schumpeterian creative destruction theory, the technology gap is one of the trigger factors influencing the degree of technology diffusion and economic growth (Castellacci, 2008; Fagerberg, 1987; Fagerberg & Verspagen, 2002). Therefore, by following the argument that technology gap may be considered as one trigger factor of technology transfer between technological leader and technological follower (Klein & Lim, 1997; Spencer, 1967; Balasubramanyam, 1973), we would like to address technology gap as an independent variable and explore how technology gap influences firms' catching up capacity in empirical studies.

Blalock & Gertler (2009) advocate that people may use the mean of three years firm total factor productivity on FDI as a baseline to measure technology gap, whilst Kokko (1994) suggests three other measurements, capital intensities, patent fees and labour productivity. Since the nature of our datasets does not provide any firm level data on patent fees or labour productivity, we cannot use them as technology gap indicator. Capital intensity, on the other hand, may confuse the boundaries of technology intensity and capital intensity in industries. That is because sometimes the capital intense industry may not be the technology intense industry, such as iron and steel or chemicals (Sjoholm, 1999). To overcome this drawback, we therefore seek an alternative method to measure technology gap. Following suggestions by (Sjoholm, 1999), we use investment ratios to measure the technology gap instead of capital intensity, presuming that the larger investment ratio, the larger difference in technologies. Therefore, to calculate the variable of investment ratio, we take the share of 'Value of Assets' which includes all tangible and intangible assets (Financial Survey Form, code 009) to the 'Number of people involved by the end of year' (Financial Survey Form, code 145).

4.3.3 Control Variables

Apart from explanatory variables illustrated in section 4.3.2, we also list various control variables which may influence decisions on innovation, collaboration and collaboration cost. The first possible determinant, which might normally be neglected by empirical studies is spillover effect which represents the size of imitation (Franco & Sasidharan, 2010).

Spillover effect, SE (j, t):

The spillover effect shows how fast rivals in a market may imitate a new innovation from the original inventor or, the possibility that a new technology leaks out. Generally speaking, these effects represent a process of copying, emulating, or stealing of other firms' technology. Some researchers (Fagerberg & Verspagen, 2002) suggest such influence may be indirect. They claim that rather than being an exogenous factor, spillover effects work on firms' catching up capacity through the technology gap. Innovation may lead to divergence of the technology gap, whilst spillover results in convergence. Besides, the higher spillover, the shorter period in which the innovator can enjoy monopoly profits and thus the more disadvantageous his position is. But others suggest that spillover effect may be considered as an exogenous factor. In North-South theory, e.g. Grossman and Helpman (1994), it is argued that imitation may directly affect firms' payoff in both current period and in the future, by not only helping the follower reduce the monopoly profits earned by the innovator from the new technology, but also spreading the new technology to the whole industry, (sometimes known as technology diffusion, Aghion, et. al, 2005, in other literatures).

It is necessary to distinguish any technology stealing effect from the product substitution effect. The previous effect is related to the market structure, which is normally affected by the business environment, such as monopoly regulations and specific industry characteristics; whilst the latter effect only depends upon differences between products normally resulting from differences in brand values or technology levels. On one hand, the spillover effect is not exactly the same as imitation, but on the other, it is to some extent one of the possible consequence of imitation and may represent the intensity of imitation.

Fagerberg (1987) suggests that the investment share, which is the percentage of gross fixed investment at the firm level compared to the industry level, may be used to measure spillover, whilst others (Bloom et al, 2007; Greenaway et al, 2004; Franco & Sasidharan, 2010) believe R&D expenditure in industries may well capture spillover effects. However, as firms normally try to protect their R&D outcomes from external excess (Slivko & Theilen, 2011), using R&D expenditure in industries may incorrectly reflect the level of the spillover effect in the industry. Inspired by Greenaway et al. (2004), we therefore employ indicators intensively related with both technology imports and technology diffusion, which are ‘expenditure on introducing technology from abroad’ (Form B107-2, code 43) and ‘expenditure on technological diffusion’ (Form B107-2, code 44) respectively. The sum of two indicators above jointly represents the imitation efforts or expenditure made by firms. Thus, the individual spillover in industries could be measured by the share of firms’ imitation expenditure on the average imitation expenditure in industries. The advantage of our measurement is that on one hand, firm’s spillover effect increases when the expenditure of technology imports and technology diffusion increases, whilst on the other hand, the firm’s spillover effect will, however, decrease, if the average imitation expenditure in industry increases. This is to say, the spillover effect may depend not only upon their own imitation expenditures, but also upon other players’ imitation efforts.

The second control variable which may play an important role in technology diffusion is transaction cost. As explained in previous chapters, high transaction costs may reduce opportunism and impact upon technology transaction or technology diffusion. It is involved in the process of negotiating, monitoring, and enforcing a contingent claims contract. However, few researchers quantify transaction cost in empirical studies (McCann et al, 2005). As Williamson (1996) stated, *'the measurement of transaction costs poses formidable difficulties'*. Therefore, bearing in mind the complexity and range of transaction cost, the methods we are using here might be considered as an approximation. To be precise, we look into transaction cost from three perspectives, the negotiation perspective, the monitoring perspective and the enforcement perspective, and by employing the following variables as indicators: market concentration (MCON); the operational personnel ratio (OPR); and complementary assets (CAST).

Market concentration, MCON (j,t)

Since market concentration increases with a reduction in the number of players, firms' transaction costs may also change with concentration as the number of players affects the complexity of the bargaining problems that players may face. Therefore, transaction costs could be reflected in the degree of market concentration (Frank & Henderson, 1992). We thus use market concentration as the indicator of transaction costs.

Market concentration, the firms' share of total industry production, also represents the degree of market competition. As illustrated in Chapter 2, there are still heated discussions on the relationship between competition and innovation, especially on the relationship between competition and collaboration. Some researchers (Oye, 1986; Coleman, 1990) suggest increasing market concentration would decrease the chance of launching new technology. But others (Cassiman et al, 2009) believe competition and innovation (collaboration) may go hand in hand. The problem is, on one hand, increasing market competition would stimulate post-innovation (collaboration) payoff, called the 'Escaping Competition' effect, whilst on the other hand, it also reduces the technology follower's incentive, called the 'Schumpeterian' effect (Aghion et al, 2005). Therefore, how firms perform when they encounter a technological change may be the result of the joint impact of the 'Escaping Competition' effect and the 'Schumpeterian' effect. Thus, although we count market concentration as a determinant of catching up, we would like to explore exactly how it works in the Chinese Manufacturing test bed.

The literature generally suggest to us three different ways to measure market concentration, which are the Concentration Ratio (CR), the Herfindahl index (HHI or simply H index) and index of industry concentration (γ index, Hennart, 1991). The first indicator, the Concentration Ratio, calculates the total output produced in an industry by a given number of largest firms in that industry (Frank & Henderson, 1992). It is common to use the largest four or largest eight firms to generate CR, so called CR_4 or CR_8 . But a high dependence on the number of largest firms chosen is also a drawback when generating CR, because it assumes there are at least four or eight firms existing in the industries. This condition may normally not always be satisfied in practice, especially for small datasets (Li et al, 2007). The second indicator, the Herfindahl index measures *'the sum of squared establishments' shares of the industry's total gross output or total employment'* (Sjoholm, 1999; Lu & Tao, 2006). Differently from CR, the advantage of the Herfindahl index is that bigger firms will be granted greater weight in the calculation of market concentration. It indicates that using H index to measure market concentration incorporates the effect of firm size. Suppose there are N firms in a particular industry. Then the algorithm for market concentration in that industry is:

$$H \equiv \sum_{i=1}^{N} Z_i^2$$

where Z_i represents the gross output (or human capital) share for firm i.

The third algorithm of market concentration, advocated by Ellison and Glaeser (1997), the index of industry concentration (γ index), is an integration of the idea of Herfindahl with the spatial Gini coefficient which measures market concentration in different geographic regions where firms are located (Krugman, 1991). Suppose there are N firms located at M different regions. The equation of market concentration is then written as:

$$\gamma \equiv \frac{G-(1-\sum_{j}^{M} x_j^2)H}{(1-\sum_{j}^{M} x_j^2)(1-H)}$$

where G, H, and x_j represented for spatial Gini coefficient, H index, and the ratio of total output (employment) in region j to total employment in the population.

However, there is a fatal drawback in this index of industry concentration. That is, if the value of the H index equals to 1 (where the market has 100% market concentration), the γ index is meaningless. In other words, the γ index is only suitable for relatively competitive industries. We therefore employ the second concept, the Herfindahl index, as the measurement of market concentration. To precisely calculate it, we use employment as a measure of firm size and obtain data from, ‘number of people involved by the end of year’

(Form 601, code M), and the 'industry code' (Form 601, code I). We first calculate total employment in different industries. Then we measure Z_i by the share of industry's employment generated by firm i. By summing up over i market, concentration is generated for each industry.

District, DIS:

In addition to any concentration effect, there may also be additional regional effects. That is to say, apart from the influence of firm size, firms locating at different regions may also affect the decision to innovate (Wang & Hao, 2011). We consider this region effect by adding another dummy variable, District.

According to data from the district section in Form 601 (code E), we know there are eight different districts in Nan Chang, which are Anyi District, Donghu District, Jinxian District, Nanchang District, Qingshanhu District, Qingyupu District, Xihu District and Xinjian District, respectively. As innovation activity may differ in a technology intense industry which mostly locates at Nan Chang National High-tech Industrial Development Zone in Qingshanhu District, we define a region dummy variable to equal to 1 when firms are geographically registered at Qingshanhu District. Otherwise, the variable, DIS, equals to zero if firms are registered at somewhere else. This setting, to some extent, may correct any region effect on market concentration and consequently help us to understand if firms locating at different areas significantly differ on their innovation strategies.

Operational personnel ratio, OPR (i,t)

Monitoring the process of technology transaction is another important function that generates transaction costs and it may involve the firm in substantial costs. Banker et al (1995) suggest that using the number of personnel in different sectors may be an effect method for measuring transaction volume. We thus employ the operational personnel ratio, measured by the ratio of 'people involved in technological management and services' (Form B107-2, code 03) to 'people involved by the end of year' (Financial Survey Form, code 145) to represent such monitoring costs.

Complementary assets, CAST (i,t)

Either the importance of complementary assets or the existence of complementary assets (specialised assets) is widely considered as an alternative way to measure transaction costs (Teece, 1986; Smith & Aldrich, 1991). Evidence shows that apart from R&D investment, complementary assets might be another important reason causing innovation failure. Controlling complementary assets must be equally important for players who develop new technology (Teece, 1986). Besides, since non-recovered assets enlarge sunk costs, their existence significantly improves trust and also decreases opportunism when two players collaborate. To measure transaction cost, we therefore also take complementary assets into account, measured by the logarithm of the sum of 'Expenditure on capital construction relating to innovation activity' (Form B107-2, code 47) and 'Price of all equipment for production and operation' (Form B107-2, code 49).

Perceived price, PP (i,t)

In Chapter 3, we discussed the effect of perceived price when building the customers' preference function. We argued that customers' decisions to purchase products depend upon the perceived price rather than the real price. Therefore, in empirical works, we also include the variable, perceived price, as one of control variables.

In our game theory model, the perceived price is explored through the discount rate of price sensitiveness. When the discount rate of price sensitiveness varies, it could directly affect consumers' perceived price which could appear to be either higher or lower than the real price. This idea was also supported by Shin (1985) who analysed the consumers' perceived price on purchasing electricity under multistep block rate schedules. He believes that since the marginal price information is costly, it is very possible to realise a higher perceived price. There are a number of arguments in the literature as to what affects the perceived price. Liu (2010) advocates that perceived price varies with three dimensions, which are communication and interaction, price expectation, and reputation and service quality, whilst Zhang et al (2007) suggest consumers' involvement with products' price information may play an important role. When consumers' target products are low technological goods, such as toothpaste, greater involvement with product price information will significantly influence consumers' perceived price, whilst when their target products are technologically intense goods, such as computers, the influence of the involvement with product price information becomes weak. On the other hand, some researchers (Campbell, 2007; Ordonez et al, 2000) claim that the major determinant of perceived price is fairness. As our datasets however do not allow us to explore further any of the ideas above, we employ other indicators to reveal perceived price instead.

Berkowitz and Walton (1980) mention that the perceived price may be influenced by perceived worth. When consumers believe it is value for money, product acceptability must increase (Winer, 1988). Therefore, to measure perceived worth, we look into the problem of product acceptability. We use the ratio of value of stocked final goods (Financial Survey Form, code 003) in annual revenue (Form 601, code O) to measure whether firm's products are welcomed by market. By comparing with other existing products in the market, a more welcomed product would normally give consumers higher utility suggesting a lower perceived (quality adjusted) price. We thus assume a negative relationship between the stock of final goods and products' acceptability, which indicates that a higher proportion of stock of final goods may lead to lower perceived worth but a higher perceived price.

Registration, REG

To test whether ownership plays an important role in innovation decisions, we also include an ownership dummy variable called registration. In the section on the type of registration in form 601 (code J), we note that there are three major registration groups: domestic assets, assets of Hong Kong, Macao, Taiwan, and foreign assets. We define a dummy variable which takes the value of 1 for all kinds of domestic ownership whilst firms in the other two major registration groups take a value of zero. This dummy variable therefore explores whether domestic firms have a higher chance of innovating or collaborating and whether their collaboration cost determinants differ from firms with other ownership.

4.4 Initial Data Exploration

In this section, we describe the data in both a general and specific sense indicating, prior to the econometric analysis in the next chapter, any revealed patterns within and across variables. Table 4.1 below summarises the particular data sources from which the various variables and constructs are derived.

Table 4.1 Variables and Indicators

Variable Type	Variables			Code	Indicators	Data code	Type
Dependent variables	Innovation			INNO (i ,t):	Innovation pattern 1-8	B107-1, code 2	binary
	Collaboration			COLL (i, t)	Innovation pattern 1-8 except 6	B107-1, code 2	binary
	Cost percentage			CP (i,t)	Ratio of firm's collaboration cost to the sum of industry average collaboration cost and firm's collaboration cost	Form B107-2, code 22 Form 601, code I	censored, percentage
Explanatory variables	Innovative ability	Innovation input	R&D	R&D (i, t):	logarithm of the sum of 'R&D expenditure' and 'expenditure on new products'	Form B107-2, code 20 Form B107-2, code 21	logarithm
		Innovation output	Patent	PAT (i, t)	sum of 'Number of applied patents' and 'Number of owned patents'	Form B107-2, code 39 Form B107-2, code 41	count
	Absorptive capacity	Education		EDUC (i,t)	Ratio of people who involved in R&D activity with qualification or higher degree to entire innovative activity group	Form B107-2, code 05 Form B107-2, code 06 Form B107-2, code 01	percentage
	Catching up capacity	Technology level		TL (i, t)	R&D expenditures per researcher	Form B107-2, code 20 Form B107-2, code 07	count
		Technology gap		TG (i, t)	Investment ratio	Financial Survey Form, code 009 Financial Survey Form, code 145	percentage
Control Variables	Spillover effect			SE (i, t)	the share of firms' imitation expenditure on average imitation expenditure in industries	Form B107-2, code 43 Form B107-2, code 44 Form 601, code I	percentage
	Transaction cost	Negotiation perspective	Market concentration	MCON (i,t)	Herfindahl index $H \equiv \sum_{i=1}^{N} Z_i^2$	Financial Survey Form, code 145 Form 601, code I	percentage
		Monitor perspective	Operational personnel ratio	OPR (i,t)	ratio of 'people involved in technological management and services' to 'people involved in by the end of year'	Form B107-2, code 03 Financial Survey Form, code 145	percentage
		Enforcement perspective	Complementary assets	CAST (i,t)	logarithm of the sum of 'Expenditure on capital construction relating innovation activity' and 'Price of all equipment for production and operation'	Form B107-2, code 47 Form B107-2, code 49	logarithm
	Perceived Price			PP (i,t)	Ratio of the value of stocked final goods in annual revenue	Financial Survey Form, code 003 Form 601, code O	percentage
	District			DIS	Equals to one for firms geographically registered at Qingshanhu District.	Form 601, code E	dummy
	Registration			REG	Equals to one for domestic assets	Form 601, code J	dummy

4.4.1 Sample Nature and Panel Characteristics

As explained above, the three years of data we employ are derived from the China Innovation Survey and Annual Corporate Financial Survey at Nan Chang, which is the capital of Jiang Xi province. However, for most people who are not familiar with the Chinese situation, having a general overview of Nan Chang's economic strength, in particular, some description of firms in this region before the data exploration would be helpful. We therefore here explore the economic background by looking into some major economic indicators for Nan Chang, Jiang Xi and China as a whole. This will also help us to understand the economic relationship and economic status between Nan Chang and Jiang Xi in China.

The economic environment

As we intend to generate a comparison across Nan Chang, Jiang Xi and China's national data, it is very important to explore the same indicators at the three levels for the years from 2005 to 2007. However, the information included in China's national year book is much less detailed than information in the province level yearbook. Some indicators in the province level yearbook, such as 'R&D human capital distribution in firms or institutions', cannot be found in national yearbooks. This indicates that the common indicators we may discuss are relatively limited. To ensure consistency in data, we therefore employ only five different indicators that commonly appeared in all three yearbooks from 2005 to 2007, which are 'GDP in local area', 'per capita GDP', 'Value of imports and exports', 'R&D expenditure', and 'Weight of R&D expenditure on local GDP'. The selection of these five indicators is based on two aspects. One is an economic aspect including three former indicators which explore local market performance, whilst the other is an R&D aspect including the latter two indicators, focusing more on innovation activity. It should be noted that, differently from our empirical firm level data in the China Innovation Survey and the Annual Corporate Financial Survey which focus on Large and Medium sized Enterprises with annual revenue at or over 50 million Yuan, the data published in all yearbooks are derived from larger scale Enterprises with annual revenue at or over 5 million Yuan. This indicates that the data from yearbooks may offer us a more general and broader view.

Table 4.2 illustrates a comparison of major economic indicators for Nan Chang, Jiang Xi and national data from 2005 to 2007, which are notated by NC, JX and N, respectively. In each cell, we list the level and the annual growth rate (in brackets). For instance, ‘NC 1007.7 (16.8%)’ in the first row in column 05 means that GDP in Nan Chang in year 2005 was 100770 million Yuan, which was 16.8% higher than GDP in 2004.

From table 4.2, we notice that in general all five indicators in that the three levels increase with time and the annual growth rates also increase. In particular, the growth rate of R&D expenditure from 2005 – 2007 exceeds 20% per annum at all three levels. We also find that the growth rate of economic performance and technological performance at lower levels is greater than at higher levels. That is to say, the indicators in Nan Chang normally performed better than in Jiang Xi province, whilst the indicators in Jiang Xi province normally performed better than China’s average level. That is probably because on the nationwide level, the economic power of Jiang Xi province is moderately strong among all China's provinces, and on the province level, as the capital of Jiang Xi province, Nan Chang has a cluster effect on manufacturing.

Table 4.2 Major Economic Indicators Comparison among Nan Chang, Jiang Xi and National Data from 2005 to 2007

Indicators	05			06			07		
GDP in local area (100 million Yuan)	NC	1007.7	(16.8%)	NC	1183.9	(17.5%)	NC	1389.9	(17.4%)
	JX	4056.8	(17.4%)	JX	4670.5	(15.1%)	JX	5500.3	(17.8%)
	N	183085	(14%)	N	211924	(15.7%)	N	249530	(17.7%)
Per capita GDP (Yuan)	NC	22390	(29.9%)	NC	26131	(16.7%)	NC	30460	(16.6%)
	JX	9440	(16.6%)	JX	10798	(14.4%)	JX	12633	(17%)
	N	14040	(13.8%)	N	16164	(15.1%)	N	18934	(17.1%)
Value of imports and exports (100 million Dollars)	NC	17.45	(30.1%)	NC	24.90	(42%)	NC	31.95	(28.3%)
	JX	40.59	(15%)	JX	61.94	(52%)	JX	94.79	(53%)
	N	14219	(23%)	N	17604	(23.8%)	N	21738	(23.5%)
R&D expenditure (million Yuan)	NC	836.8	(42%)	NC	1315.2	(57%)	NC	1688.5	(28.4%)
	JX	3157.7	(35%)	JX	4362.1	(38%)	JX	5476.1	(25.5%)
	N	245000	(24.6%)	N	300300	(22.6%)	N	366400	(22%)
Weight of R&D expenditure on local GDP	NC	0.83%	(22.1%)	NC	1.11%	(33.7%)	NC	1.21%	(9.0%)
	JX	0.79%	(16.2%)	JX	0.94%	(19.0%)	JX	1.00%	(6.4%)
	N	1.34%	(9.8%)	N	1.42%	(6.0%)	N	1.47%	(3.5%)

We now analyse economic strength in more details by discussing each indicator in Table 4.2. From the indicators 'GDP in local area' and 'Per capital GDP', we found the per capita GDP in Nan Chang is dramatically greater than in both Jiang Xi province and China as a whole. However, although the GDP level in Nan Chang is higher than the China's average level, the GDP level in Jiang Xi province is slightly lower. This indicates that our target datasets reflect a mid-income and moderate developing region with intensive growth potential.

There are 33 provinces[10] in China. We find that although the growth rate of imports and exports in Jiang Xi (and in Nan Chang) increased dramatically each year, the imports and exports level in Jiang Xi (and in Nan Chang) are still extremely low. This fact indicates that the main markets of firms in Jiang Xi tend to be local. However, targeting local markets does not necessarily mean less

[10] The term 'province' in this thesis refers to provincial level division, which is the basic unit in the China Statistical Yearbook. To be precise, it includes 22 provinces, 4 municipalities, 5 autonomous regions and 2 special administrative regions.

competitiveness. Firms may still compete with others in any province in China, although this information may not be obtained from statistical yearbooks.

The last two indicators in Table 4.2 are designed to look at the R&D aspect. In particular, the 'total R&D expenditure' measures the amount of R&D effort in each region by absolute value, whilst the 'weight of R&D expenditure on local GDP' reveals the R&D effort through relative value. From the data in the fourth row, we found that R&D investment at all levels increased dramatically from 2005 to 2007. The lowest growth rate of R&D expenditure was 22%, whilst the biggest rate exceeds 57%. As innovation output is normally positively associated with the innovation input, we assume there exists significant growth in innovation and collaboration in the annual data in Nan Chang. But on the other hand, from the low value of the indicator that 'weight of R&D expenditure on local GDP', we realised the efforts of R&D input in both Nan Chang and Jiang Xi are still limited, although the growth rate of R&D input exceeds the average national level.

Panel data characteristics

Although the above is informative it is worth noted that the data that we employ in our empirical analysis does differ in at least two basic ways. Firstly, datasets derived from forms B107-1 and B107-2 contain completely different types of data. The former collects data on all projects undertaken by firms, whereas the latter describes the general innovation activity of firms. Any one firm may have several innovation projects underway within a time period and projects may even extend beyond a single time period. Secondly as our approach is concerned with the innovative activity of firms our emphasis is upon data related to the firm. The panel of firms included within our sample is thus based on the responses to form B107-2.

Using form B107-2, our sample (which is also the population) of Large and Medium sized firms for the three years from 2005 to 2007 is 79, 79 and 86 respectively. The panel is thus unbalanced. As some firms left the sample (the market), whilst others joined, the panel contains 103 different firms within 3 years and 244 observations (ID * Time) in total. As a simple picture of the history of these firms shown in Table 4.3, approximately 62% of firms are in the sample for all 3 years, whilst about 11.7% (7.77%+3.88%) of firms successfully survived for continuous 2 years. We note that 10% of firms existed for only the first period while nearly 13% of firms were created in the last period. These results suggest that the manufacturing industry in Nan Chang is intensely competitive. A comparison of survival rates suggest that the market elimination ratio decreased as time proceeded which may reflect the result of a maturing market environment, including legislation encouraging patent protection order in recent years.

Table 4.3 Descriptions of Panel Data Sample

Pattern of observed firms	Observation number	Observation percentage
Observed in all three years (***)	64	62.14
Observed in the last year (• • *)	13	12.62
Observed in the first year (* • •)	10	9.71
Observed in the last two years (• **)	8	7.77
Observed in the first two years (** •)	4	3.88
Observed in the middle year (• * •)	3	2.91
Observed in the first and last year (* • *)	1	0.97
Total	103	100

Using form B107-2, we can provide a breakdown of the data by year and by 2-digit industries. However, there is still considerable controversy in the literature about whether one should select by 2-digit industry code or 4-digit industry code. On one hand, some researchers (Swartz & Aronson, 1967) claim that since 4-digit industry code may well group firms with similarities, using 4-digt industry code could decrease the bias against rejection of the null hypothesis and generate more powerful comparisons. On the other hand, however, some results reveal that the benefit of employing 2-digit industry code may outweigh its drawbacks (Tomiura, 2009).

Since the ISIC industry structure is based on firms' similarities, using a 4-digit industry code may severely limit any indication of firm diversification (Mills & Schumann, 1985; Bowen et al, 1982). Firms apparently appear more diversified using a 2-digit industry classification than a 4-digit classification. In particular, for firms producing various but similar products which are located in the same 2-digit industry but different 4-digit industry codes, using 2-digit industry codes may avoid selection bias by considering the diversification of firms. Secondly, Wernerfelt and Montgomery (1988) advocate that the average profitability across 2-digit industry is a better measure of performance than which at the 3-digit or 4-digit level. Thirdly, some financial researches on stock prices suggest that estimates of the industry effect is insensitive to whether 2 or 4 digit industry classifications are used (King, 1966; Kahle & Walking, 1996). Last but not least, to the best of our knowledge, all empirical works related to Chinese manufacturing are based on 2-digit industry[11] codes (Luo & Cao, 2005; Lu & Tao, 2006; Li et al, 2007; Wang & Hao, 2011; Bai, 2011). We therefore also classify our data using 2-digit industry codes rather than 3 or 4 digit industry code.

[11] Though the industry classification in these researches is based on 2-digit industry, most of their data are derived from province level rather than firm level.

Table 4.4 shows the total number of sample firms in each year and in each 2-digit industry. The sum over industries for each year equals the number of observations in that year: e.g.79 and 86 for 2005 and 2007 respectively. Figure 4.1 illustrates the distribution of the number of firms by year and by industry based on the data from table 4.4. According to the manufacturing structure Table in appendix, we found that most firms are in technology intensive industries. In particular, from table 4.4, we notice that in certain industries, there is only one firm. However, following the general discussion of data from table 4.2, this does not necessarily mean that there is no competition in the market and the local market is a monopoly. Nor does it mean that just because there is only one firm recorded that the firm will not collaborate. This is partly because our data are derived from Large and Medium sized firms with annual revenue at or over 50 million RMB. All other firms, such as up-scale firms with lower annual revenue and small firms, are not investigated. The firms may also compete or collaborate with firms based elsewhere or even overseas. However as we do not have any knowledge of nationwide firm level datasets, we cannot discuss these issues further.

Table 4.4 Sample Industry Breakdown: 2005-2007

Industry	2005	2006	2007	Industry	2005	2006	2007	Industry	2005	2006	2007
13	3	3	4	24	0	0	0	35	2	2	2
14	4	4	4	25	0	0	0	36	6	6	8
15	3	2	3	26	6	5	3	37	4	4	5
16	1	1	1	27	8	8	8	39	10	8	8
17	5	5	6	28	1	1	1	40	1	2	1
18	1	2	1	29	1	1	1	41	0	0	0
19	0	0	0	30	0	0	0	42	0	0	1
20	0	1	1	31	4	3	3	43	0	0	0
21	0	0	0	32	2	2	2	44	8	8	8
22	1	1	1	33	2	2	3	45	0	0	1
23	4	4	4	34	2	3	5	46	0	1	1

Figure 4.1 Sample Distribution of Firms

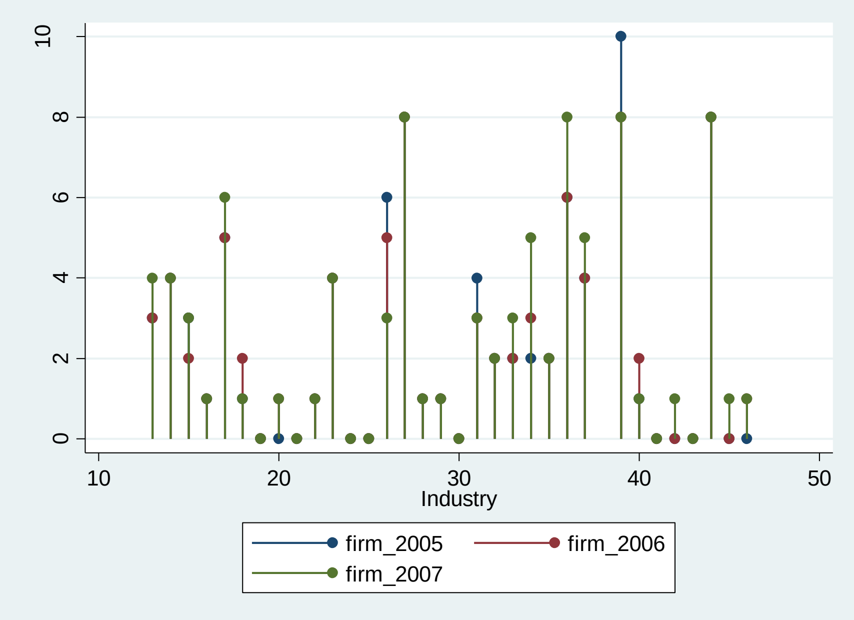

Table 4.5 indicates the average sample number of firms per industry for each of the sample years (based on 33 and not 26 industries). The data show that on average, there were approximately 2.4 firms in each industry. The number would be slightly higher if 'empty' industries were removed from the sample. The maximum number of firms recorded in an industry falls from 10 in 2005 to 8 in 2006 and 2007. Given that the number of observations increases from 79 in 2006 to 86 in 2008 this might mean that over time the inter industry spread of firms in Nan Chang is becoming more equal. Result from Table 4.9 below also confirms this.

Table 4.5 Description of Number of Firms by Industry

Year	Number of industries	Average number of firms in each industry
2005	33	2.393939
2006	33	2.393939
2007	33	2.606061

4.4.2 Data Exploration of Technology Changes

The data sources provide considerable details upon the nature of innovative activity. To better understand the scope of technology changes (including both self-innovation and collaboration) in the sample, we detail the innovation variable by different characteristics. Table 4.6 illustrates the breakdown of innovation projects from form B107-1 by ‘innovation nature’, ‘innovation pattern’, ‘innovation usage’ and ‘innovation target’ for each year 2005 to 2007. The figures in each cell show the count number for each group, whilst the numbers in the brackets represent the weight of innovation in that group relative to the population. For instance, in the first row, first column, ‘21 (4.6%)’ means that 21 projects are national projects, representing 4.6% of all projects reported in 2005. One important point we need to address is that firms are allowed to pick only one type of classifications when they fill in the survey form. We did not observe any project with two or more types in any classification. That is to say, for instance in the case of innovation patterns, firms could only choose one specific pattern from the eight choices. There is no way that a project is classified as involving both self-innovation and collaboration with institutions, or a project involves collaboration with both universities and institutions.

Table 4.6 Innovation Projects Breakdown upon Different Means of Classification

Innovation Nature	05	06	07
1. National Project	21 (4.6%)	13 (2.5%)	17 (3.0%)
2. Local Project	17 (3.7%)	41 (7.9%)	51 (8.9%)
3. Entrusted Project by other firms	63 (13.7%)	13 (2.5%)	16 (2.8%)
4. Self Project	357 (77.6%)	450(86.5%)	478(83.7%)
5. Project from abroad	2 (0.4%)	3 (0.6%)	7 (1.2%)
6. Others	0 (0%)	0 (0%)	2 (0.4%)
Innovation Pattern	05	06	07
1. Collaboration with abroad institutions	2 (0.4%)	25 (5.4%)	2 (0.4%)
2. Collaboration with national universities	29 (6.3%)	9 (1.7%)	21 (3.7%)
3. Collaboration with national independent institutions	15 (3.3%)	26 (5%)	24 (4.2%)
4. Collaboration with registered foreign investments	1 (0.2%)	0 (0%)	1 (0.2%)
5. Collaboration with registered other investments	24 (5.2%)	29 (5.6%)	41 (7.2%)
6. Innovation by self research department	252 (54.8%)	214(41.2%)	248(43.4%)
7. Collaboration with local government	134 (29.1%)	213(41%)	215(37.7%)
8. Others	3 (0.6%)	4 (0.8%)	19 (3.3%)
Innovation Usage	05	06	07
1. Fundamental research	0 (0%)	0 (0%)	0 (0%)

	05	06	07
2. Applied research	1 (0.2%)	1 (0.2%)	1 (0.2%)
3. R&D	269 (58.5%)	332(63.8%)	405(70.9%)
4. Applied R&D	190 (41.3%)	187(36%)	165(28.9%)
Innovation Target			
	05	06	07
1. To develop brand new product	190 (41.3%)	176(33.8%)	232(40.6%)
2. To increase functions of existing product	84 (18.3%)	60 (11.5%)	64 (11.2%)
3. To improve performance of product	54 (11.7%)	101(19.4%)	131(22.9%)
4. To increase productivity	45 (9.8%)	63 (12.1%)	89 (15.6%)
5. To decrease energy consumption	15 (3.3%)	21 (4.0%)	20 (3.5)
6. To decrease raw materials consumption	8 (1.7%)	30 (5.8%)	9 (1.6%)
7. To decrease pollution	12 (2.6%)	22 (4.2%)	10 (1.8%)
8. Others	52 (11.3%)	47 (9.0%)	16 (2.8%)

From Table 4.6, we observe that the total number of all types of innovation projects increases from 460 in 2005, to 520 in 2006, and 571 in 2007. The growth in the number of innovation projects, especially the increment in 2006, may be the cause of increase in the R&D input recorded in Table 4.2. On average, more than 80% of innovation projects are 'self-projects', which indicates that firms have a strong self-incentive to pursue technology changes. In contrast, projects arranged by central government or local government are relatively limited

The innovation pattern section in Table 4.6 reveals that nearly half the innovation projects are counted as self-innovation, and half are considered to be collaborative projects. We find in general, both the size and the relative importance of self-innovation are lower in the year 2006 and 2007 compared to 2005. This result shows that firms in Nan Chang have greater tendency to collaborate in recent years. The data also shows that both 'collaboration with registered foreign investments' and 'collaboration with registered other investments' is relatively small. The majority of collaboration occurs between firms and local government, which represents more than 30% of all innovation projects. This is partly because local government sometimes supplies R&D

funding for certain projects. Moreover, firms intending to innovate often need policy support from local government, such as schemes to attract talented people[12]. This is one of the examples why the game theoretic model may not strictly apply to collaboration in China for that model only addresses collaboration with other firms while intensive collaboration with local government is obviously present in our data. Similarly, in Chapter 5, innovation and collaboration is defined to include these joint activities between firms and local government.

The results in the innovation usage section in Table 4.6 show that nearly 99.8% of innovation projects may be considered as either R&D or applied R&D, i.e. at the more 'close to market' end of the spectrum. The last section of Table 4.6 addressing innovation targets indicates whether the innovation projects are regarded as product innovations or process innovations. According to the Oslo Manual (OECD, 1996), product innovation is innovation which will result in technologically new products '*whose technological characteristics or intended uses differ significantly from those of previously produced products'*, or technologically improved products offering *' improved ………….performance or lower cost through use of higher-performance components or materials, or a complex product'.* We therefore classify four of the groups in the innovation target section as product innovation. These include: 1. To develop brand new product'; '2. To increase functions of existing product'; '3. To increase efficiency of products'; and '7. To decrease pollution'. Activities directed at the other targets are considered to be process innovation. The data shows that more than

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12 'Housing Benefits for Attracting Highly Skilled People', [2003]31; and 'Measures for Introducing National Highly Talented People', [2003]41

70% of innovation projects involve product innovation. In particular, in 2007, the proportion of product innovation reaches 76.5%. This indicates that the majority of projects intend to invent or significantly improve products and this tendency has been increasing in recent years. However, as the variable ‘innovation’, measures all kinds of innovation activities, both product innovation and process innovation are to be investigated in Chapter 5, which is another reason we may not replicate the above game theoretic model empirically.

Table 4.7 Breakdowns of Innovation and Collaboration upon Ownership and Region

		Innovation		
		05	06	07
Ownership	Domestic Assets	32 (40.5%, 50%)	35 (44.3%, 56.5%)	34 (39.5%, 52.3%)
	Assets of Hong Kong, Macao, Taiwan	3 (3.8%, 50%)	3 (3.8%, 50%)	4 (4.7%, 66.7%)
	Foreign Assets	3 (3.8%, 33.3%)	5 (6.3%, 45.5%)	5 (5.8%, 33.3%)
Region	Qingshanhu District	20 (25.3%, 54%)	25 (31.6%, 62.5%)	24 (27.9%, 60%)
	Other Districts	18 (22.8%, 42.8%)	18 (22.8%, 46.1%)	19 (22.1%, 41.3%)
Total		38 (48.1%)	43 (54.4%)	43 (50%)
		Collaboration		
		05	06	07
Ownership	Domestic Assets	21 (26.6%, 32.8%)	23 (29.1%, 37.1%)	25(29.1%, 38.5%)
	Assets of Hong Kong, Macao, Taiwan	2 (2.5%, 33.3%)	3 (3.8%, 50%)	3 (3.5%, 50%)
	Foreign Assets	2 (2.5%, 22.2%)	2 (2.5%, 18.2%)	4 (4.7%, 26.7%)
Region	Qingshanhu District	15 (19.0%, 40.5%)	18 (22.8%, 45%)	18(20.9%, 45%)
	Other Districts	10 (12.6%, 23.8%)	10 (12.6%, 25.6%)	14(16.3%, 30.4%)
Total		25 (31.6%)	28(35.4%)	32(37.2%)

The above data are all project based. In Table 4.7 we look at firms rather than projects and explore the pattern of innovation and collaboration across firms by looking into the ownership of innovative firms and their regional location. Similar to Table 4.6, Table 4.7 presents data upon both extent and proportions for the period from 2005 to 2007. Numbers in each cell are a count of the number of innovative (or collaborating) firms, whilst the two numbers in brackets indicate the proportion (i) of firms in the sample population, and (ii) in the sample with the same pattern, respectively. For example, ‘32 (40.5%, 50%)’ in the first row first column means that 32 firms that are domestic assets innovated, representing 40% of all firms in the sample and 50% of all domestic firms.

Table 4.7 indicates that in general, nearly half of the firms undertake innovation, whilst more than 30% of firms undertake collaboration. These two figures jointly indicate that more than 60% of firms must choose collaboration when they innovate. Another general observation is that firms seem to have a growing preference for collaboration over time. Whereas 31.6% of firms choose collaboration in 2005, the figure decreased to 35.4% in 2006 and 37.2% in 2007. Bearing in mind that the percentage of sample firms who innovate in 2007 is only 50%, this indicates that the proportion of firms undertaking self-innovation must have decreased in 2007

In terms of ownership, Table 4.7 suggests that of the around 50% of all firms that innovate, about 40% of all firms are (i.e. eight tenths of those who innovate) are domestic assets. Of the 35% or so of all firms that collaborate, about 30% are domestic assets. The data indicate that firstly 80% of firms which choose to innovate or to collaborate are domestic assets. It also indicates that more than 70% of domestic firms choose collaboration as their innovation pattern. In particular, we notice that the percentage of domestic collaborative firms, increases from 26.6% in 2005 to 29.1% in 2007, suggesting that as time proceeds, more and more domestic firms choose collaboration. On the other hand, innovative firms that are Assets of Hong Kong, Macao, Taiwan or foreign assets, although similar to each other, form only a small proportion of innovators and collaborators in the sample population.

However, we may not simply claim that firms that are domestic assets are more likely to innovate or to collaborate. This is because the low percentage of non-domestic innovator or collaborators in the sample may be caused by the low number of non-domestic firms in sample. By comparing with the second percentage in brackets, we find that although the percentage of innovative or collaborative firms from Hong Kong, Macao, or Taiwan in the total population is relatively low, the percentage of innovative or collaborative firms within the group containing firms from Hong Kong Macao, Taiwan is quite large. This indicates that both domestic assets and the assets of Hong Kong, Macao, Taiwan are highly likely to innovate or collaborate. In contrast, no matter whether we look at the percentage of firms in the sample population, or in the sample of foreign firms, the desire for innovation or collaboration in foreign firms is significantly low. This might be because most foreign firms located in Nan Chang are not headquarters, and they will normally focus more on marketing rather than R&D activities.

Apart from ownership, we can also explore the innovation and collaboration distribution across all firms by districts. Since most of the technology intensive industries are located at Qingshanhu District, we divide our sample into two parts: firms located at Qingshanhu District and firms located at the seven other districts. Table 4.7 shows that there are about 24 or so innovative firms located in the Qingshanhu District (about 28% of all sample firms) and 18 or so innovative firms located in the other districts. Similarly about 18 collaborating firms (about 23% of all sample firms) are located in the Qingshanhu District and about 10 or 14 in the other districts. These results indicate that more than 55% of firms who innovate are located at Qingshanhu

District, whilst more than 65% of firms who collaborate are located at Qingshanhu District. Also, it suggests that more than 72% of innovative firms in the Qingshanhu District choose collaboration as their innovation pattern.

On the other hand, looking at the proportion of innovative or collaborative firms in a specific region relative to all firms in that specific region (the second percentage in brackets), we observe that 54% of firms in the Qingshanhu District innovate, whilst only 41% of firms in other districts innovate. Similar phenomenon may also be observed re collaboration in that the proportion of firms locating at Qingshanhu District who collaborate is nearly one third higher than in in other districts. This result indicates that firms locating at Qingshanhu District are more likely to innovate or collaborate.

4.4.3 Data Exploration on Other Variables

As listed above, in our empirical analysis the main dependent variables are innovation (INNO), collaboration (COLL) and collaboration cost percentage (CP), whilst the independent variables are concerned with three issues, innovative ability including both innovation input (R&D) and innovation output (PAT), absorptive capacity represented by education (EDUC), and catching up capacity, which encompasses the technology level (TL) and the technology gap (TG). In addition, we also employ several control variables including the spillover effect (SE), transaction cost (MCON, OPR, CAST), perceived price (PP), a district dummy variable (DIS) and a registration dummy variable (REG). In this sub-section, we firstly present descriptive statistics using pooled data (covering all three years) and then the balanced data (covering firms observed in all three years) for these explanatory variables. Then the sample is broken down by year and industry to provide further details.

The summary statistics in Table 4.8 illustrate the mean values for variables in different samples. All the independent variables and control variables are included. As indicated in Table 4.3, market size varies as some firms joined and some firms left the sample. We therefore explore mean values for both unbalanced and balanced samples, which include 244 observations and 192 observations respectively. The results shows that, for example: nearly 37% and 42% of employees have engineering qualifications or a higher degree in unbalanced and balanced sample; the mean value for the spillover effect, measured as the ratio of the firms' imitation expenditure relative to average imitation expenditure in the industry, is 0.28 in the unbalanced sample, and 0.34 in the balanced sample, which is relatively small; the mean value for MCON is about 0.39 indicating generally high market concentration; and from the means of DIS and REG, we know that on average, 48% of firms are located in the Qingshanhu district and 78% of firms are recognised as domestic assets.

Table 4.8 Means of Variables in Sample Data

	Unbalanced Mean	Balanced Mean
R&D	2.019	2.344
PAT	3.672	4.505
EDUC	0.367	0.422
TL	58.68	65.83
TG	516.9	535.7
SE	0.279	0.335
MCON	0.392	0.380
OPR	0.0210	0.0242
CAST	4.858	4.980
PP	0.0713	0.0742
DIS	0.480	0.474
REG	0.783	0.781
N	244	192

There are seven industries that are not represented in our population sample as demonstrated in Table 4.4 and thus our industry breakdowns cover only the other 26 industries in the sample population and 21 industries in the balanced sample. Table 4.9 presents descriptive statistics for a number of the independent variables by year and industry. The results from unbalanced data show that, in general, the sample covers more firms and more industries as time passes. We also observe considerable heterogeneity in the sample with firms in some industries being more innovatively active (R&D), or having a higher catching up capacity.

Table 4.9 Mean Value of Explanatory Variables by Industry and Time

Industry	R&D	PAT	EDUC	TL	TG	R&D	PAT	EDUC	TL	TG	R&D	PAT	EDUC	TL	TG
								Unbalanced							
	2005					**2006**					**2007**				
13	0	0	0	0	498.6	1.574	1	0.333	46.89	768.2	1.136	0.5	0.157	16.65	633.8
14	1.942	0	0.5	17.24	267.2	2.007	0	0.317	21.17	253	2.114	0.5	0.436	130.2	649.6
15	1.226	3.333	0.1486	0	331.6	1.985	5	0.242	0	687.3	1.401	3	0.133	29.53	724.4
17	0.8966	0	0.0521	13.22	171.1	0.8774	0.2	0.103	17.4	144.3	0.724	0.167	0.083	12.24	131.7
18	0	0	0	0	430.2	0	0	0	0	252.8	0	0	0	0	874.1
22	0	0	0	0	3293	0	0	0	0	3416	0	0	0	0	3031
23	0.8618	3.25	0.1981	42.61	280.7	0.7867	2	0.139	38.94	268.3	0.67	2.75	0.151	10.88	713.6
26	1.263	0	0.2485	33.89	299.7	1.427	0	0.275	22.22	334.9	1.422	0.333	0.486	46.12	312.4
27	3.664	13	0.6385	191.2	386.3	3.587	8.125	0.669	144.7	449.9	3.668	16	0.674	119.5	455.8
28	3.117	0	0.5256	8.384	765.1	3.063	0	0.624	6.8	817.6	2.978	0	1	22.61	631.5
29	3.511	0	0.9909	14.73	665.1	3.633	0	0.955	32.57	735.4	3.668	0	0.659	52.95	8863
31	0.8696	0	0.25	0	305.5	2.056	0	0.635	0	391	2.086	0	0.667	0	462.7
32	4.796	1	0.466	103.9	385.7	4.572	1	0.48	65.9	486.7	4.819	1	0.535	156.3	551.9
33	3.83	1.5	0.7583	49.66	400.2	4.123	1.5	0.591	90.37	422.1	2.797	0	0.469	92.46	870.2
34	2.151	9.5	0.4243	22.93	551.9	2.518	10.33	0.625	15.66	483	0.78	0.2	0.314	9.272	419.9
35	4.064	3.5	0.7481	14.42	367	4.083	2.5	0.769	22.67	379.5	4.156	2.5	0.872	19.24	422.8
36	2.191	1.166	0.4163	19.73	133.7	2.219	1.166	0.366	26.35	149.4	2.207	0.75	0.356	31.53	166.1
37	2.837	7.75	0.2812	162.7	465.6	2.911	10.25	0.294	142.7	695.8	2.357	9	0.247	139.1	663.8
39	1.341	4.4	0.2164	39.6	408.1	1.949	6.875	0.463	49.18	416.8	2.689	9.25	0.362	266.6	480.3
40	5.088	40	0.5169	66.96	252.2	4.303	11.5	0.497	53.65	227.6	5.197	28	0.553	88.5	204.5
44	0.8642	0	0.33	0	589.1	0.942	1	0.229	0.3523	601.1	0.527	1	0.369	3.151	617.9
16	4.554	0	0.7432	285.5	2371	4.699	6	0.667	231.4	509.7	4.017	7	0.516	49.66	915.4
20						0	0	0	0	884.9	4.713	16	0.236	358.7	502
46						4.565	2	0.849	469.3	1744	0	0	0	0	874.4
42											0	0	0	0	99.77
45											0	0	0	0	964.8
Number of firms: 79						Number of firms: 79					Number of firms: 86				
	Balanced														
13	0	0	0	0	498.6	1.574	1	0.333	46.89	768.2	1.514	0.667	0.21	22.2	761.7
14	1.942	0	0.5	17.24	267.2	2.006	0	0.317	21.17	253	2.114	0.5	0.436	130.2	649.6
15	1.838	5	0.2229	0	446.8	1.985	5	0.241	0	687.3	2.101	4.5	0.199	44.29	952.6
17	1.1208	0	0.0652	16.52	169.3	1.096	0.25	0.129	21.75	149.6	1.085	0.25	0.124	18.36	145.4
18	0	0	0	0	430.2	0	0	0	0	431.1	0	0	0	0	874.1
22	0	0	0	0	3293	0	0	0	0	3416	0	0	0	0	3031
23	0.8618	3.25	0.1981	42.61	280.7	0.7866	2	0.139	38.94	268.3	0.67	2.75	0.151	10.88	713.6
26	2.525	0	0.497	67.79	279.4	2.378	0	0.458	37.04	291.4	1.421	0.333	0.486	46.12	312.4
27	3.711	14.85	0.6583	199.6	391.1	3.626	9.285	0.693	147.1	450.3	4.191	18.28	0.77	136.5	486.1
28	3.116	0	0.5256	8.384	765.1	3.062	0	0.624	6.8	817.6	2.977	0	1	22.61	631.5
29	3.51	0	0.9909	14.73	665.1	3.633	0	0.955	32.57	735.4	3.668	0	0.659	52.95	8863
31	1.739	0	0.5	0	345	1.515	0	0.48	0	415.8	1.518	0	0.5	0	414.3
32	4.795	1	0.466	103.9	385.7	4.571	1	0.48	65.9	486.7	4.819	1	0.535	156.3	551.9
33	3.83	1.5	0.7583	49.66	400.2	4.123	1.5	0.591	90.37	422.1	4.196	0	0.703	138.6	557.3
34	4.301	19	0.8486	45.87	949.3	3.907	31	0.876	47	748.8	3.901	1	0.876	46.36	993.3
35	4.063	3.5	0.7481	14.42	367	4.082	2.5	0.769	22.67	379.5	4.156	2.5	0.872	19.24	422.8
36	2.191	1.166	0.4163	19.73	133.7	2.218	1.166	0.366	26.35	149.4	2.942	1	0.474	42.04	157.9
37	5.674	15.5	0.5624	325.4	636.8	5.822	20.5	0.589	285.5	786.9	5.893	22.5	0.619	347.8	947.6
39	1.915	6.285	0.2454	56.57	363.7	2.226	7.857	0.529	56.21	459.7	3.074	10.57	0.413	304.7	542.3
40	5.088	40	0.5169	66.96	252.2	5.167	23	0.561	82.39	250	5.197	28	0.553	88.5	204.5
44	0.8642	0	0.33	0	589.1	0.9419	1	0.229	0.3523	601.1	0.527	1	0.369	3.151	617.9
Number of firms: 64						Number of firms: 64					Number of firms: 64				

In terms of the innovation output variable, represented by PAT (patent), we find that this reaches highest for firms in industries 40 (Manufacture of radio, television and communication equipment and apparatus), 37 (Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment), 34 (Manufacture of basic metals), 27 (Manufacture of pharmaceuticals, medicinal chemical and botanical products) and 39 (Manufacture of electrical machinery and apparatus n.e.c). To some degree this may be because these five industries have been recognised as pillar industries by the Jiang Xi government since 2003 (Dai et al, 2011), and firms in these industries might have further financial support for R&D and also benefit from preferential policies. But on the other hand, we found that in some industries, patent performance may not significantly increase with large amounts of R&D input, such as industry 33 (Mining of non-ferrous metal ores) and 14 (Manufacture of food products). This result therefore suggests that judgements regarding the firms' innovative ability may actually vary with different measures.

Results for the variable EDUC (education) reveals that a higher proportion of employees with higher degrees may be found in industry 16 (Manufacture of tobacco products), 29 (Manufacture of rubber products) and 35 (Manufacture of machinery and equipment n.e.c). This suggests that firms in these industries may have higher absorptive capacity. However, as only one firm is reported in the dataset (which only covers large and medium enterprises) for both industries 16 and 29, the actual value for the proportion of employees with higher degrees in both industries could be much lower in reality

On the other hand, from Table 4.9, we observe that variables TL and SE appear to take a zero value for a number of industries. This is partly because the measures of technology level and spillover effect are closely related to R&D and imitation expenditure. Not every firm is involved in innovation or imitation and hence TL and SE in those firms are zero. Another reason may be the uneven distribution of innovative activity among firms. In some industries, only one firm spends a large amount of expenditure on imitation, whilst others do not. This means that spillover in this firm must be greater than in others.

4.4.4 Variable Correlations

To provide a general picture of the relationship between the three dependent variables and various independent variables, a table of partial correlations is provided (Table 4.10). Partial correlation (different from unconditional correlation) allows one to explore the influence of one particular independent variable on the dependent variable while holding all other variables constant. Partial correlation thus eliminates the impacts of other variables and only represents the individual influence of each independent variable. Another important point we should bear in mind is that since both collaboration and collaboration cost will only occur when firms innovate, any correlation between one variable and collaboration (or collaboration cost) must be conditional. To explain this, for instance, we may look at the partial correlation between SE (spillover effect) and CP (collaboration cost) in the unbalanced sample. The result from Table 4.10 suggests SE is positively correlated with CP, but is not significantly related with INNO (innovation). We cannot consequently claim that CP must increase when SE increases. Instead, we may suggest that when firms decide to innovate via collaboration, their collaboration cost percentage share may be elastic to a change in SE.

Table 4.10 Partial Correlation of Dependent Variables

	Unbalanced			Balanced		
	INNO	COLL	CP	INNO	COLL	CP
R_D	0.8031***	0.0983	0.2445***	0.7713***	0.0417	0.2496***
PAT	-0.2136***	-0.0392	0.0166	-0.2109***	-0.037	0.004
EDUC	0.5543***	0.3816***	0.1335**	0.5765***	0.4087***	0.1189
TL	-0.1425**	0.1209*	-0.1343**	-0.1163	0.1227*	-0.1309*
TG	0.0084	0.1067	0.0573	0.017	0.0662	0.0448
SE	0.0058	-0.0614	0.1536**	0.0193	-0.0652	0.138*
MCON	-0.0159	-0.04	-0.0662	-0.0144	-0.0556	-0.0751
OPR	-0.0993	0.1047	-0.0424	-0.0345	0.1544**	-0.036
CAST	-0.0382	0.1292**	0.1005	-0.0489	0.1877**	0.1217
PP	0.0667	-0.0246	-0.2086***	0.0719	0.0297	-0.2002***
DIS	0.0093	0.0915	-0.0575	-0.0051	0.0574	-0.0638
REG	0.0544	0.113*	0.0414	0.0493	0.0621	0.0245

Note*:* * p<0.10, ** p<0.05, *** p<0.01

According to Table 4.10, two variables are commonly seen to be significantly correlated with the three dependent variables in most cases, ‘education’ (EDUC) and ‘technology level’ (TL). In particular, the results show that ‘education’ is positively related to innovation, collaboration and collaboration cost (except for the collaboration cost model in the balanced sample), suggesting that firms having more employees with higher degrees innovate more and collaborate more. They also seem to pay more of the cost when they collaborate. On the other hand, the ‘technology level’ has a negative influence on innovation and collaboration cost, but is positively related to collaboration at the 10% significance level. This indicates that technological leaders are not necessarily the most innovative and that they pay less of collaboration costs (when they collaborate which they are more likely to do).

Two other variables are significantly related to innovation. They are R&D, and ‘patent’ (PAT), both of which are indicators for firms’ innovative ability. But interestingly, whilst R&D is positively correlated with innovation, PAT is negatively related. Also, the results from Table 4.10 reveal that apart from ‘education’ (EDUC) and ‘technology level’ (TL), collaboration is positively correlated to both ‘complementary assets’ (CAST) and ‘registration’ (REG) in the population sample (which means that firms that spend more on complementary assets or (and) domestic assets tend to collaborate more), whilst it is positively correlated with both CAST and OPR (operational personnel ratio) in the balanced sample, (suggesting that firms may be more likely to collaborate when transaction costs from a monitor perspective or an enforcement perspective increase). Last but not least, we found that collaboration cost is positively correlated with ‘R&D’, ‘education’ (EDUC) (but not in the balanced sample) and the ‘spillover effect’ (SE), but negatively correlated with ‘technology level’ (TL) and ‘perceived price’ (PP).

Such results, of course, provide only an initial view of the patterns that are apparent in the date. Correlation analysis in particular assumes linear relationships and may be problematic when there are data selection issues. Therefore in the next Chapter more sophisticated approaches are employed to analyse these data by using a set of various econometric models.

4.5 Conclusion and Indications

Together with Chapter 5, in this chapter by using Chinese empirical data, we empirically explore under what circumstances firms prefer to innovate and/or collaborate, and how collaboration costs are shared. These data in particular discuss what empirical relationships may exist, demonstrate the nature of the data and conduct some initial investigations of what determinants may influence innovation and collaboration.

As we have explained before, the theoretical approach developed in the previous chapter does not neatly transfer to the real world context. For example in the game theory model, collaboration was defined as the collaboration between competing rival firms. The data for the Chinese region studied however indicated that most collaboration activities have been between firms and local government (Table 4.6). Given the institutional context to work with our data, the definition of collaboration in this and the next chapter has been expanded to incorporate collaborations with all players, including firms, institutions and government. Secondly, when we do observe collaborations between firms, those firms may not necessarily be competing. They may be rivals, or sometimes may be upstream or downstream of each other so we have to look at this wider picture rather than narrowing ourselves in a rigid mode. Thirdly, the game theoretic model concentrated upon product innovation while our data however shows that firms undertake both product and process innovation. We have thus decided to consider both types of technological change. The empirical analysis in this sense may not closely replicate the game theory modelling, but this is considered preferable to taking the wider real world lens rather than the narrow theoretical lens.

This approach also means that there has been some shifting of definitions as we move from theory to empirics which has been discussed in detail before. One of the most important however is that we have found it useful to consider in the empirical work that innovation encompasses both self-innovation and innovation through collaboration. While in the theoretical work innovation was considered to be just self-innovation (i.e. the introduction of new products without collaboration).

This work merits recognition as the first to use micro level data on Large and Medium sized firms to investigate innovation and collaboration strategies of firms in China (and in fact in any mid-income level developing country). The work itself has been constrained by the limitations given by the confidential nature of the data and the Statistics Law of the People's Republic of China. The dataset is composed of two surveys, four forms, covering 33 manufacturing industries from 2005 to 2007 located in Nan Chang, which is one of fastest growing cities in both Jiang Xi province and in China. The number of sample firms (also the population) increases from 79 in 2005 and 2006 to 86 in 2007. We found that the firms are mainly in chemical and electrical related industries (ISIC 26 to 44), where innovations also occur intensively.

Following the game theory model, we define three dependent variables: 'innovation', 'collaboration' and 'collaboration cost'. The game theoretic framework however is not particularly useful as a guide to defining and measuring those variables that may be considered as explanatory. Using recent relevant literatures (Castellacci, 2008; Blalock & Gertler, 2009), we thus approach the definition of such variables by exploring the innovative ability, absorptive capacity, and catching up capability of firms and define variables that measure these concepts. In addition and more closely related to the theory, we also take 'transaction cost', and 'perceived price' into account as control variables.

The results that are generated are new and provide details on innovation and collaboration patterns in Chinese manufacturing industry that have not been reported before. We find that an increasing proportion of the sample (population of) firms has been innovating over time, rising from 48% to 50% in the sample period. We also observe that self-innovation decreases in importance over time (to 43%) with collaborative innovation increasing. Most innovation projects are concerned with either ‘R&D’, or ‘applied R&D’, rather than fundamental or applied research whilst more than 70% of innovation could be counted as product innovation.

The results from Table 4.9 suggest that the distribution of innovation activities varies significantly across industries. Firms in ‘pillar industries’ (code 40, 37, 27, 34, and 39) are more innovatively active, whilst firms in industry 16, 29 and 35 seem to have greater absorptive capacity.

Correlation analysis in Table 4.10 show that, of the three factors posited to affect innovation, collaboration and shares of collaboration costs, i.e. innovative ability, absorptive capacity, and catching up capability of firms, there is a correlation between at least some of the variables representing each of these factors for innovation and collaboration cost, but only absorptive capacity and catching up capacity are significantly correlated with collaboration. In more details, the results suggest that since the correlation coefficient of ‘education’ is consistent and positive for nearly all dependent variables, firms with better educated employees tend to exhibit more innovation, are more likely to collaborate and bear a higher share of collaboration cost when they do undertake collaboration. In addition we found that increasing transaction cost may significantly stimulate collaboration, whilst increasing imitation or decreasing perceived price may significantly increase collaboration cost share. In the next Chapter, we will continue to analyse the sample data by employing econometric as opposed to statistical methods.

Appendix

1. China Innovation Survey

1.1. Innovation Project Form (Form B107-1)

Firm Code: XXXXXX-X
Firm Name(with Stamp): XXXXX

Project Number	Project Name	Innovation Nature	Innovation Pattern	Innovation Usage	Innovation Target	Starting Date	Finishing Date	No. of People involved in project	with engineering qualification	without engineering qualification but with higher degree	No. of involved working hours	Internal project expense this year
A	B	1	2	3	4	5	6	7	8	9	10	11

Director of Project: XXXX Tel: XXXX Submitted Date: XXXXX

Category Classifications:

(1). Innovation Nature Classification and Subcode

Subcode	Innovation Nature Classification	Details
1	National Project	Including 863 projects, Xinghuo projects, Pandeng projects..
2	Local Project	Including projects hold by local governments
3	Entrusted Project by other firms	
4	Self-Project	
5	Project from abroad	
6	Others	

(2). Innovation Pattern Classification and Subcode

Subcode	Innovation Pattern Classification
1	Collaboration with abroad institutions
2	Collaboration with national universities
3	Collaboration with national independent institutions
4	Collaboration with registered foreign investments
5	Collaboration with registered other investments
6	Innovation by self-research department
7	Collaboration with local government
8	Others

(3) Innovation Usage Classification and Subcode

Subcode	Innovation Usage Classification
1	Fundamental research
2	Applied research
3	R&D
4	Applied R&D

(4) Innovation Target Classification and Subcode

Subcode	Innovation Target	Details
1	To develop brand new product	To design or produce brand new products by adopting new technology or disciplines
2	To increase functions of existing product	
3	To improve performance of product	
4	To increase productivity	
5	To decrease energy consumption	
6	To decrease raw materials consumption	
7	To decrease pollution	
8	Others	

1.2. Innovation Activity Form (Form B107-2)

Firm Code: XXXXXX-X
Firm Name (with Stamp): XXXXX

Name of Index	**Units**	**Code**	**Annual Spending**
A	B	C	1
1. Information of Innovation Activity			
(1). People involved in Innovation Activity		01	
Inc. people directly involved in projects		02	
people involved in technological management and services		03	
Inc. women		101	
Inc. full time employees		04	
Inc. people with engineering qualification		05	
without engineering qualification but with higher degree		06	
Inc. people involved in R&D		07	
(2). Funding Collection Resource	¥1,000	08	
Self funding	¥1,000	09	
Loan from financial institution	¥1,000	10	
Government	¥1,000	11	
Public sectors	¥1,000	53	
Abroad	¥1,000	12	
Others	¥1,000	13	
(3). Funding Expenditure	¥1,000	14	
Internal expenditure	¥1,000	15	
Divided by usages:			
Service charge inc. salaries	¥1,000	16	
Raw materials	¥1,000	17	
Equipment purchase	¥1,000	18	
Others	¥1,000	19	
Inc. R&D expenditure	¥1,000	20	
Inc. Expenditure on new products	¥1,000	21	
External expenditure by collaboration	¥1,000	22	
Inc. Expenditure with universities and institutions	¥1,000	23	
Other firms	¥1,000	24	
2. Annual Information of All Innovation Projects			
Number of innovation projects		25	
Inc. projects of inventing new products		26	
Inc. projects of R&D		27	
Internal expenditure of all projects	¥1,000	28	
Inc. expenditure on R&D	¥1,000	29	
3. Information of Self-Funded Research Institutions			
Number of research institutions		30	
People in research institutions		31	
Inc. people with doctoral degrees		32	
with master degrees		33	
Internal expenditure in self funded research institutions	¥1,000	34	
Price of all equipment	¥1,000	35	
Name of Index	Units	Code	Annual Spending
4. Innovation Activity Output			
Output value of new products	¥1,000	36	
Revenue from new products	¥1,000	37	
Inc. revenue from export	¥1,000	38	
Number of applied patents		39	
Inc. invention patent		40	

Number of owned patents		41
5. Information and Means of Obtained Technology		
Expenditure on improving existing technology	¥1,000	42
Expenditure on introducing technology from abroad	¥1,000	43
Expenditure on technological diffusion	¥1,000	44
Expenditure on purchase national technology	¥1,000	45
6. Other Information		
Number of engineers and technicians		46
Expenditure on capital construction relating innovation activity	¥1,000	47
Inc. expenditure on civil construction	¥1,000	48
Price of all equipment for production and operation	¥1,000	49
Inc. electronic controlled rack	¥1,000	50
Tax deduction for innovation activity	¥1,000	51
P.S. Number of self-funded research institutions abroad		52

Director of Project: XXXX Tel: XXXX Submitted Date: XXXXX

1.3. Corporate Details Form

Form No.601
Form producer: National Bureau of Statistics of China

Firm Code: A
Firm Name: deleted
Legal Person: deleted
Place of Firm Registered: ,Administrative Code B ,Province C ,City D , District E
Contact Details: Tel: ,Fax: ,Email: , Website:
Industry Classification: Major Products (Major Activity): 1. F; 2. G; 3. H Industry Code: I

Type of Registration: J

Domestic Assets:
110. National
120. Collective
130. Shareholding System
141. National Affiliated
142. Collective Affiliated
143. International Affiliated
149. Other Affiliated
151. National Proprietorship
159. Other Limited Liability Company
160. Joint Stock Limited Partnership
171. Private Proprietorship
171. Private Partnership
173. Private Limited Liability Company
174. Private Joint Stock Limited Partnership
190. Others

Assets of Hong Kong, Macao, Taiwan
210. Joint Venture with Hong Kong, Macao, Taiwan
220. Cooperation with Hong Kong, Macao, Taiwan
230. Proprietorship of Hong Kong, Macao, Taiwan
240. Joint Stock Limited Partnership with Hong Kong, Macao, Taiwan

Foreign Assets:
310. International Joint Venture
320. International Cooperation
330. International Proprietorship
340. Joint Stock Limited Partnership of Foreign Investments

Firm Attribution: K

10. Nation
20. Province
40. City
50. Prefecture
61. Street
62. Town
63. Country
71. Village
90. Others

Time of Found (Year): L
Number of People Involved by the End of Year: M

Inc. Female:	N
Firm Major Indicators	
Annual Revenue:	O
Inc. Annual Revenue from Major Products(Major Activity):	P
Value of Assets:	Q
Firm Director:	
Tel:	

2. Annual Corporate Financial Survey

Firm (Organisation) Code: XXXX	Form Designed by NBS
Firm Name: XXXX	Valid until: 2011

Name of Index	**Units**	**Code**	**Annual Spending**
Stock	¥1,000	002	
Including Final Goods	¥1,000	003	
Value of Assets	¥1,000	009	
Annual Revenue from Major Products(Major Activity)	¥1,000	124	
Annual Cost from Major Products(Major Activity)	¥1,000	125	
Profit	¥1,000	136	
Number of People Involved		145	

3. Details of Manufacturing Structure

Division	Description
13	Manufacture of agricultural byproducts
14	Manufacture of food products
15	Manufacture of beverages
16	Manufacture of tobacco products
17	Manufacture of textiles
18	Manufacture of wearing apparel
19	Manufacture of leather and related products
20	Manufacture of wood and of products of wood and cork, except furniture;
21	Manufacture of furniture
22	Manufacture of paper and paper products
23	Printing and reproduction of recorded media
24	Manufacture of office, accounting and computing machinery
25	Manufacture of coke and refined petroleum products
26	Manufacture of chemicals and chemical products
27	Manufacture of pharmaceuticals, medicinal chemical and botanical products
28	Manufacture of man-made fibres
29	Manufacture of rubber products
30	Manufacture of plastics products
31	Manufacture of other non-metallic mineral products
32	Mining of coal and lignite; extraction of peat
33	Mining of non-ferrous metal ores
34	Manufacture of basic metals
35	Manufacture of machinery and equipment n.e.c.
36	Manufacture of fabricated metal products, except machinery and equipment
37	Manufacture of motor vehicles, trailers, semi-trailers and other transport equipment
39	Manufacture of electrical machinery and apparatus n.e.c.
40	Manufacture of radio, television and communication equipment and apparatus
41	Manufacture of medical, precision and optical instruments, watches and clocks
42	Other manufacturing
43	Recycling
44	Electricity supply
45	Gas supply
46	Water supply

5 The Determinants of Collaboration in Innovation in Chinese Manufacturing Industry: An Empirical Analysis

5.1 Introduction

This chapter employs various econometric techniques to further investigate the determinants of innovation (including innovation via collaboration), collaboration and collaboration cost sharing in Chinese manufacturing. In Chapter 3, a theoretical model was use to explore what determinants may impact collaboration and collaboration cost. In chapter 4, the sources and summary statistics for the data to be used in this chapter have been explored in depth. Here we test various hypotheses as to the factors that influence firms' technological change decisions, including innovation, collaboration and collaboration cost respectively. In particular, for the first time in the literature, we empirically investigate the determinants of cost shares in technological collaborations. The econometric analysis provides some clear insight and consequently enables one to draw relevant implications for policy makers.

A number of predictions relating to the determinants of collaboration and collaboration cost are generated from the game theory model in Chapter 3. However, as explained in Chapter 4, due to the nature of the Chinese economy, there are numerous reasons why we cannot simply move from those predictions to empirical testing. Thus, instead of testing the empirical validity of hypotheses derived from the game theory model, here we intend to propose a series of other related but also testable hypotheses which are either generated from existing literatures or implied from our theoretical model.

In section 5.2 we summarise the possible impacts of a number of variables on three different dependent variables discussed in the previous chapter and generate various testable hypotheses. Section 5.3 examines issues relating to any problems of selection bias in the empirical analysis. Using both balanced and unbalanced samples we show that there are no significant problems relating to selection bias. We hence proceed in Section 5.4 by estimating equations for each dependent variable separately. In particular, we employ a Probit model to regress the binary choice between innovation and collaboration, whilst we use OLS, fixed effect and random effect panel models to regress collaboration cost. Section 5.5 further investigates dependent variables by considering both timing and dynamic issues. The contribution of the estimates and limitations are explained in the final section of this chapter.

5.2 Hypotheses and Empirical Research Questions

The definition and measures of dependent and independent variables, taken from the previous chapter, are reproduced in Table 5.1.

Table 5.1 Variables Table

	Variables		**Definition**	**Literature**
DV	Innovation	INNO (i ,t)	Innovation pattern 1-8	
	Collaboration	COLL (i, t)	Innovation pattern 1-8 except 6	
	Cost percentage	CP (i,t)	Ratio of firm's collaboration cost to the sum of industry average collaboration cost and firm's collaboration cost	
IDV	Innovative ability	Innovation input: R&D (i, t)	logarithm of the sum of 'R&D expenditure' and 'expenditure on new products'	Davidson & Segerstrom, 1998 Fagerberg, 1987 Castellacci, 2008
		Innovation output: Patent, PAT (i, t)	sum of 'Number of applied patents' and 'Number of owned patents'	Fagerberg & Verspagen, 2002
	Absorptive capacity	Education EDUC (i,t)	Ratio of people who involved in R&D activity with qualification or higher degree to entire innovative activity group	Blalock & Gertler, 2009 Castellacci, 2008
	Catching up capacity	Technology level TL (i, t)	R&D expenditures per researcher	Ryu & Byeon, 2011 Canova, 2004
		Technology gap TG (i, t)	Investment ratio	Klein & Lim, 1997 Sjoholm, 1999

Note*:* DV and IDV represent dependent variables and independent variables, respectively.

As stated above we are unable to move directly from the game theoretic model to estimation (for example, to do so would require that we were able to separate out action/reaction and persistent dominance markets from each other which we are unable to do). Instead, by looking at the patterns of innovation and collaboration in Chapter 4 and considering related literatures we specify three factors as our determinants of innovation and collaboration, which are innovative ability, absorptive capacity and catching up capacity. We choose these three factors partly because they are all closely related to technological growth, but more importantly, they cover both endogenous and exogenous impacts on innovation and collaboration. For instance, the former two factors, including R&D, PAT (patent), and EDUC (education) are influences concerned with firms own ability, whilst the last factor, catching up capacity (including TL (technology level) and TG (technology gap)) emphasise more on the influence of the market. Most literatures support a positive relationship between these five determinants and innovation (collaboration) (last column in Table 5.1), but it is rare to see empirical works that tests them in a general way. Rather than discussing the individual impacts of these five independent variables on technology change, we therefore employ them as measures of the three trigger factors in a broad sense and focus on how they influence innovation, collaboration and collaboration cost.

Thus, we illustrate six *ad hoc* hypotheses that are worthy of further investigation. These hypotheses may be stated as follows

H1: A firm with high innovative ability is more likely to innovate.
H2: A firm with high absorptive capacity is more likely to innovate
H3: A firm with high catching capacity is more likely to innovate
H4: A firm with high innovative ability is more likely to collaborate
H5: A firm with high absorptive capacity is more likely to collaborate
H6: A firm with high catching capacity is more likely to collaborate.

These six hypotheses fall naturally into two groups (Table 5.2). The first group (third column of Table 5.2) encompasses H1, H2 and H3 and investigates whether innovative ability, absorptive capacity or catching up capacity significantly influence innovation. The second group (fourth column of Table 5.2) contains the other hypotheses and analysis on in what circumstance firms decide to collaborate, and thus provides insight into the determinants of collaboration.

We proxy innovative ability though both innovation input, R&D, and innovation output, PAT (patent). We assume increasing either R&D, or PAT will increase firms' innovative ability, leading to a higher possibility of innovation and collaboration (H1 & H4). Measuring firms' absorptive capacity by EDUC (education level), we hypothesise that increasing EDUC must result in growth of innovation and collaboration (H2 & H4). Finally, as both TL (technology level) and TG (technology gap) are indicators of firms' catching up capacity, we expect a positive relationship between TL, TG and innovation or collaboration (H3 & H6).

There is little empirical research relating to the cost sharing issues and thus we have little knowledge about the determinants of cost sharing when firms collaborate. The existing literature only provides little guidance on how to proceed. On the other hand, all the predictions relating to collaboration cost sharing generated from our game theory model are for the technological follower. Although this contributes to the existing literature, in empirical practice, it is difficult to identify which players are actually the low technology firms and which are the high-technology firms. We thus restrict our empirical analysis of collaboration costs to explore the impact of only those determinants which we have argued influence innovation and collaboration decisions to see if they also play an important role in collaboration cost sharing decision. We thus use all five independent variables as regressors for each of the dependent variables. This is summarised in Table 5.2.

Table 5.2 Empirical Hypotheses

		INNO (Innovation)	COLL (Collaboration)	CP (Collaboration cost)
R&D PAT	Innovative ability	H1: +	H4: +	?
EDUC	Absorptive capacity	H2: +	H5: +	?
TL TG	Catching up capacity	H3: +	H6: +	?

5.3 Pooled Selection Models and Estimations

5.3.1 Econometric Models for Sample Selection

There are two main empirical questions. The first one is the determinants of collaboration in innovation (COLL), whist the other is the determinants of the collaboration cost percentage (CP). Clearly however, only those firms that innovate may undertake collaborative activities. It is therefore necessary to consider that collaboration in innovation means that two events have occurred: firstly the firm has innovated (INNO) and secondly the firm has collaborated in this innovation. For any firm chosen at random, the absence of collaboration may mean either there was no innovation or that there was innovation but no collaboration. If we were to proceed by just looking at the incidence of collaboration in the whole sample of firms rather than just a sample of innovating firms then our estimates may tend to show bias in the estimates of what impacts upon collaborative activity and its costs.

Appropriate ways to approach such issues econometrically depend upon whether the dependent variable is observable and whether it is exogenous. To be more specific, if the collaboration decision is exogenous and observable, whist other independent variables are observable, then we have a censored variable estimation structure (even though in some cases, censored variables are not necessary). If collaboration is exogenous and observable, but the only condition of independent variables' observability is that the innovation decision must be observable, then what we need is a censored Tobit model. However, if the innovation decision depends upon some unobserved factors, then we need a selection model to first group our sample before analysing the determinants of collaboration cost percentage. We may then choose a Probit selection model for the first part of our data exploration[13].

The selection Tobit model, also called a type Ⅱ Tobit model (Amemiya, 1985), was first used to explore the relationship between wage rates and rates of labour participation (Gonau, 1974), but is now well known as the Heckman (1979) correction procedure (which was initially developed for correcting for selectivity bias in linear regression with normal errors). The difference between the Heckman model and other Probit models is that the censored data which probably affect the observed dependent variable, are also endogenous. Therefore, the Heckman correction, as in Probit models, can not only deal with the binary information carried by latent variables, but also solve the bias problem during the selection process. The Heckman method via the Heckit has been widely used in much social science empirical analysis, in particular in agriculture and politics (Bratti et. al, 2004; Yen and Shonkwiler, 1999;

13 Even though the Probit selection model is especially good at dealing with unobserved information by Probit models, it is still considered as one kind of Tobit models.

Schaffner, 2002; Mbata, 2001; Busch and Reinhardt, 2000; Grier et. al, 1994; Nie et.al, 2007).

However, one concern is that the Heckman procedure explores the sample via pooled estimation, thereby not taking full advantage of the benefits of panel data. To solve this problem, some researchers suggest using multilevel modelling techniques as an alternative method to regress either selection models, or panel models (Rabe-Hesketh et al, 2005; 2006; Miranda & Rabe-Hesketh, 2006). But research rarely investigates panel data selection models. Rabe-Hesketh (2002) advocates an idea that a panel data selection model may be estimated by one particular kind of multilevel model, labelled the Generalized Linear Latent And Mixed Models (GLLAMM) which defines the outcome model as nested in the selection model and both cross sectional models are again nested in time order. However, to the best of our knowledge, as the GLLAMM technique has not been actually fully applied in practice, adopting GLLAMM techniques to regress a panel selection model does not seem sufficiently convincing. We therefore proceed by using the conventional Heckman selection procedure to investigate any selection bias.

Prior to undertaking empirical analysis, we first address the structure of the Heckman model and the differences between the two Heckman selection methods: the General Heckman model and Heckman Probit sample selection model.

5.3.1.1 General Heckman models.

In this section, we consider a sequence of random vectors, $\{(X_i, Y_i), i = 1,..., n\}$ including one pair of models $Y_i = (Y_{i1}, Y_{i2})$ where X_i is a K vector of covariates, whilst Y_i represents the response regression models. In particular, we let Y_{i1} indicate the outcome model for cost percentages (CP) and Y_{i2} for the observable collaboration decision (COLL). Then

$$Y_{i1} = X_{i1}\beta_1 + \varepsilon_1 \quad \text{when } Y_{i2} = 1$$
$$Y_{i2} = \begin{cases} 1, if\ Y_{i2}^{*} = X_{i2}\beta_2 + \varepsilon_2 > 0 \\ 0, otherwise \end{cases}$$

where β_i is the coefficient vector for $X_{ij}(j=1,2)$. In particular, if Y_{i2}^{*} is greater than zero, then the firm collaborates, otherwise, Y_{i2} equals to zero, and no collaboration happens. The observed decisions, Y_{i1}, Y_{i2} ,depend not only upon several explanatory variables, but also on unknown error terms, ε_{1i} , ε_{2i} . In particular, $\varepsilon_1, \varepsilon_2$ are assume to obey the following two assumptions:

$$(\varepsilon_1, \varepsilon_2 | X_{i1}, X_{i2}) \sim N(0,0,\sigma_1,1,\rho_{12});$$
$$E(X_{ij}|\varepsilon_1) = 0;\ E(X_{ij}|\varepsilon_2) = 0$$

The above assumptions indicate that the error term in the selection model is iid but has a correlation ρ_{12} with the outcome model's error, which causes the bias. One uses selection models to avoid the impact brought about by such correlated errors. When $\rho_{12} = 0$, there is no correlation between errors, which consequently indicates no bias addressed through selection. The cost percentage model then turns out to be a standard regression model, whilst the collaboration model is a standard Probit model.

5.3.1.2 Heckman Probit sample selection models

Similar to the general Heckman models, Probit sample selection models also comprise two models. However, both of them are binary models with censored data.

$$Y_{i2} = \begin{cases} 1, if\ Y_{i2}^{*} = X_{i2}\beta_2 + \varepsilon_2 > 0, \& when Y_{i3} = 1 \\ 0, otherwise \end{cases}$$
$$Y_{i3} = \begin{cases} 1, if\ Y_{i3}^{*} = X_{i3}\beta_3 + \varepsilon_3 > 0 \\ 0, otherwise \end{cases}$$

The binary outcome Y_{i2} can only be observed when condition $Y_{i3} = 1$ is met. Consider, Y_{i2} , Y_{i3} as the outcome equation and selection equation, respectively. Since the collaboration decision is made only if the firm innovates, the possibility of event of Y_{i2} (collaboration, COLL) is less than Y_{i3} (innovation[14], INNO). Thus, the previous estimation solution is no longer suitable for a bivariate Probit case[15].

The assumptions of the Probit selection models must thus follow:

$$(\varepsilon_2, \varepsilon_3 | X_{i2}, X_{i3}) \sim N(0,0,1,1,\rho_{23});$$

$$E(X_{ij}|\varepsilon_2) = 0;\ E(X_{ij}|\varepsilon_3) = 0 \text{ i,j=1,2}$$

Similar to the general Heckman models, in bivariate models, variables X_{ij} are independent with errors. In particular, if the error correlation $\rho_{23} = 0$, it indicates that there is no selection bias between the collaboration Probit model and the innovation Probit model.

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14 Here we are referring to a broad sense of innovation, equivalent to 'technology change' in both Chapter 4 and Chapter 5.

15 We use STATA syntax *'heckprob'* instead of 'heckman'

There are two main approaches to estimate using the Heckman procedure. One is ML estimation in which one estimates the parameter vectors and error correlation model sets together by maximizing the log likelihood function, whilst the other approach is Two Step estimation (also known as the Heckit approach) where one calculates a selection correction term from the selection equation in the first step, and at the second stage, adds it into the outcome equation as an 'omitted variable' (Heckman, 1979). In STATA, instead of using the general Heckman estimation, the default estimation options set for the Heckman Probit selection model is ML estimation, because the conventional method of two-step estimation in Probit selection models does not generate a consistent result. We therefore employ the ML estimator for both the Heckman selection model and the Heckman Probit selection model.

5.3.2 Results and Discussions for Bivariate Models

To analyse the collaboration cost percentage (CP), there are prior conditions on collaboration (COLL) and innovation (INNO) to be met. If there is no selection bias between collaboration and innovation, we may directly test the selection bias between collaboration cost and collaboration. But if there is selection bias between collaboration and innovation, then we must take this extra bias into account when we investigate selection bias between collaboration cost and collaboration. In that case, the selection of collaboration cost from collaboration may have a double bias effect. Thus, before moving to a selection bias investigation between collaboration cost and collaboration, we must firstly estimate the Binary Probit selection model sets (collaboration and innovation) to see if there is any bias arising from the selection process. Then we report an analysis of general Heckman models with collaboration and collaboration cost percentages as dependent variables.

In particular, we investigate selection bias not only by using the complete (unbalanced) sample containing all firms, but also using samples including only those firms observed for all the three sample years (the balanced sample). The benefit of doing this is, by comparing the selection bias models with both unbalanced and balanced samples, the conclusions on selection bias tend to be more robust.

The results for the bivariate selection models of collaboration and innovation are presented in Table 5.3. Two models are investigated with different sample sizes. As we explained in Chapter 4 (Table 4.1 & Table 5.1), since firms investment in R&D may be coterminous with innovation, adding variables measuring R&D expenditures as determinants of innovation may be misleading. The problem is that adding the perfectly predicted variables into Probit models may dramatically decrease the measured impacts of other variables. However, this problem does not exist when we model COLL (collaboration). Because, different from innovation, R&D expenditures in projects do not necessarily result in collaboration. To explore unobserved determinants, we therefore exclude all variables containing R&D in the models relating to the dependent variable INNO (innovation) but keep such variables as independent variables in the estimation of collaboration and collaboration cost. Thus, the variables we may drop are R&D and TL (technology level) which are respectively measured by 'logarithm of R&D expenditures and expenditures on new products' and 'R&D expenditures per researcher'. In addition, to make sure that heteroskedasticy does not in validate our models, all covariance matrices are estimated using robust errors to control the possible problems caused by heteroskedasticty. As White (1980) suggested, these robust standard errors are consistent ‘even if the residuals are heteroscedastic’ (Hoechle, 2007).

Table 5.3 Results of a Selection Model of Collaboration and Innovation

	Unbalanced	Balanced
COLL		
R&D	-0.194	-0.182
	(-1.25)	(-1.17)
PAT	0.00402	0.00410
	(0.45)	(0.46)
EDUC	1.399**	1.385**
	(2.26)	(2.13)
TL	0.000480	0.000479
	(0.42)	(0.42)
TG	0.00165***	0.00159***
	(3.36)	(3.18)
Constant	-0.585	-0.585
	(-0.75)	(-0.74)
INNO		
PAT	5.356***	5.936***
	(13.92)	(15.90)
EDUC	5.008***	5.005***
	(5.07)	(3.85)
TG	0.0000540	0.0000499
	(0.64)	(0.59)
Constant	-1.992***	-1.842***
	(-10.76)	(-8.28)
athrho	0.386	0.373
	(0.90)	(0.80)
N	244	192
Log likelihood	-93.07	-81.94
Wald Chi2	0.806	0.647
Prob>Chi2	0.369	0.421

Note*:* Robust standard errors are used to control heteroskedasticty
* p<0.10, ** p<0.05, *** p<0.01

The results from Table 5.3 show that EDUC (education) and TG (technology gap) are significantly positively related to collaboration in both the unbalanced and balanced samples, whilst PAT (patent), and EDUC (education) are significantly positively related to innovation in both the unbalanced and balanced samples. This confirms positive relationships between absorptive capacity and innovation and collaboration. It also confirms a positive relationship between catching up capacity and collaboration and a positive relationship between innovative ability and innovation. This indicates that increasing employees with a highly educated background is equally important to both innovation and collaboration. But increasing innovative ability is more important to innovation, whilst increasing catching up capacity is more important to collaboration.

The last row of Table 5.3 represents the correlation between the errors of the outcome model and selection model, ρ_{12}, which would be the cause of selection bias. The null hypothesis of the Heckman selection models is that $\rho_{12} = 0$, meaning no correlation between the errors of two models. However, all the Chi square statistics reveal, for each of the Heckman Probit sample selection models, that one cannot reject the null hypothesis, as statistically, estimating the collaboration equation without allowing for the sample selection bias would not cause any bias in the estimates of that equation. We may therefore estimate the collaboration and innovation equations individually.

Table 5.4 Results of a Selection Model of Collaboration Cost and Collaboration

	Unbalanced	Balanced
CP		
R&D	0.0239	0.0210
	(0.55)	(0.50)
PAT	-0.00139	-0.00158
	(-0.52)	(-0.59)
EDUC	0.337***	0.300***
	(1.26)	(1.06)
TL	0.000254	0.000303
	(1.06)	(1.18)
TG	-0.0000214	-0.0000265
	(-0.96)	(-1.32)
Constant	0.0281	0.0720
	(0.08)	(0.19)
COLL		
R&D	0.291***	0.255***
	(3.16)	(2.62)
PAT	-0.00149	0.000263
	(-0.14)	(0.02)
EDUC	2.302***	2.292***
	(5.53)	(5.24)
TL	0.000575	0.000578
	(0.62)	(0.63)
TG	0.000592***	0.000545***
	(3.46)	(3.10)
Constant	-2.646***	-2.495***
	(-9.46)	(-8.19)

athrho	-0.291	-0.306
	(-0.68)	(-0.69)
lnsigma	-1.091***	-1.066***
	(-14.02)	(-12.78)
N	244	192
Log likelihood	-102.1	-94.79
Wald Chi2	0.465	0.481
Prob>Chi2	0.495	0.488

Note: Robust standard errors are used to control heteroskedasticty
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Similarly, employing general Heckman models, any selection bias between CP (collaboration cost percentage) and COLL (collaboration) is investigated using different sample sizes. Again, to control any heteroskedasticty problem, robust standard errors are computed. The results in Table 5.4 reveal that R&D, EDUC (education), and TG (technology gap) are significantly positively related to collaboration, whilst only EDUC is significantly positively related to collaboration cost. The high p value suggests that the assumption of no correlation of errors between the selection model and the outcome model cannot be rejected, indicating there is no selection bias between collaboration cost and collaboration. In the next section, we may therefore estimate models with dependent variables CP and COLL by using panel data and Probit methods respectively.

5.4 Initial Analysis of Dependent Variables

As shown in Table 5.3 and Table 5.4 as there are no sample selection bias issues to be observed between collaboration and innovation and between collaboration cost and collaboration, we can explore determinants for each of the dependent variables individually, setting aside the sample selection problem. On the other hand, due to the causality relationship between collaboration and innovation, and between collaboration cost and collaboration, when we analyse innovation, collaboration or collaboration costs, we do not include other dependent variables as regressors.

Since both variables COLL (collaboration) and INNO (innovation) have discrete binary outcomes, rather than employing a linear panel model, we need to employ a panel probit regression model. While, for dependent variable CP (collaboration cost), which is a continuous variable, we employ OLS model and both fixed effect and random effect panel data models.

However, similar to section 5.3, prior to undertaking empirical analysis, we first address the structure of each model, which, in particular, will inform analysis of timing and dynamic issues later in the analysis.

5.4.1 Econometric Models: Initial Analysis

There are several forms of binary outcome (or dummy variable) panel models. The most commonly used approaches are the Logistic model and the Probit model, which both estimate the continuous possibility of an event occurring using sigmoid curves. The main difference between the Logistic model and the Probit model is that the former allows for a logistic distribution, whilst the Probit model allows for a normal distribution. As the normal curve approaches the axis more quickly than the logistic curve, the Logistic model has flatter tails. In general, the results of the two models are quite similar if sample sizes are large However, for smaller sample sizes, the Probit model tends to perform better. We thus employ the Probit approach to estimate models of the two binary dependent variables, COLL (collaboration) and INNO (innovation):

$$\Pr(Y=1|X)=\Pr(X^{'}\beta+\varepsilon_i>0)=\Phi(X^{'}\beta)$$

where $\varepsilon_i \sim N(0,1)$; $\Phi(.)$ is Cumulative Distribution Function (CDF) of standard normal distribution.

The latent dependent variable Y can only be observed when its value is greater than zero. Standard assumptions are that the error term in the Probit model follows a normal distribution and is uncorrelated with all independent variables.

On the other hand, for the non-binary response variable, CP (collaboration cost), we need to seek for other appropriate panel data models. In terms of the nature of the dataset, the panel only covers only three years, which is short and thus represents a case of a micro panel or short panel case. For most micro panel analysis, we observe that linear fixed effect models or random effect models are commonly used in the existing literature. For instance, Kalirajan (1991) examined the effect of new rice technology in 30 farms locating in the Southern Indian district of Coimbatore from 1983 to 1986. Arnberg and Bjorner (2007) explored the degree of substitution between energy, labour and machine capital by employing four years fixed effect panel data in Denmark. Khalifah and Adam (2007) employed both fixed and random effect models with four years manufacturing data to detect productivity spillovers from FDI in Malaysia. By using three years' firm level data in Peru, Jackle and Li (2006) revealed the relationship between firm dynamics and institutional participation. We therefore also use fixed and random effect models to analyse CP in our micro panel. In particular, for a better comparison between fixed and random effect models, a pooled OLS estimation may also be adopted.

Fixed effect models are designed to explore the unique time-invariant characteristic which is unobserved within an entity (firms, countries, persons) in intercepts, by assuming identical slope and constant variance across entities. When those characteristics exist, they may cause bias to the predictors or the outcome variables. To observe the net effect caused by other independent variables, we therefore must control these time-invariant characteristics to force the model to fit its assumption. The structure of fixed effect model is thus:

$$Y_{it} = X_{it}^{'}\beta + \alpha_i + u_{it}$$

where α_i is the unknown intercept for each entity, whilst u_{it} is the error term.

One thing that needs to borne in mind is that because the unobserved time-invariant characteristic captures individual effects, it means that the unknown intercept and errors should not be correlated with other individual characteristics. If the errors between different entities correlate, the fixed effect may not be appropriate. The random effect model, on the other hand, assumes the unobserved characteristics are random and uncorrelated with predictors and independent variables, assuming the same intercept and slope. That is to say, in random effect models, all X_{it} are treated as exogenous. The structure of the random effect model is:

$$Y_{it} = X_{it}^{'}\beta + \alpha_i + u_{it} + \varepsilon_{it}$$

where u_{it} represents the errors between entities, whilst ε_{it} stands for the errors within entities.

In fact, the main difference between the fixed effect model and random effect models is whether the unobserved characteristics are included in the intercept. If they are, this is a fixed effect model. If they are treated as part of the error term, the model is a random effect model.

5.4.2 Results and Discussions: Initial Analysis

The results of estimating Probit models for the dependent variables INNO (innovation) and COLL (collaboration) are represented in Table 5.5 and 5.6. We estimate all models using the maximum likelihood approach. All models formulate a likelihood ratio test to test the hypotheses that several coefficients are simultaneously zero. We first regress models containing both independent and control variables. Then, we adopt a parsimonious procedure by dropping the least significant regressors, one by one, until all remaining variables are significant, or until dropping a variable significantly reduces the explanatory power of the regression. The advantage of using parsimonious model is that *'they prevent the researcher from consciously or subconsciously manipulating the model so that it over-fits the available facts'* (Gabaix & David, 2008).

Model 1 marked as full model in Table 5.5 is the model including all independent variables and control variables, whilst model 2 is the parsimonious model. We use bootstrap standard errors with 50 times replications to control for heteroskedasticity[16], whose performance is reported as effective in small samples (Godfrey, 1998; Fu et at, 2005). Also, to better explore despite the limitations of the sample size, all results listed in the initial analysis are generated from the unbalanced population. The likelihood ratio results suggest that all these Probit models are valid.

[16] All models using bootstrap standard errors in this chapter are based on bootstrap standard errors with defaulted 50 replications in STATA.

Table 5.5 Probit Model for Innovation

	Full model	Parsimonious
	1	2
PAT	6.576	
	(0.01)	
EDUC	7.006***	10.57***
	(2.82)	(3.80)
TG	-0.000499	
	(-0.53)	
SE	1.431	
	(0.77)	
MCON	0.0824	
	(0.04)	
OPR	-3.771	
	(-0.39)	
CAST	0.335	
	(0.52)	
PP	9.481*	
	(1.78)	
DIS	0.171	
	(0.23)	
REG	0.525	
	(0.54)	
Constant	-5.469	-3.363***
	(-1.50)	(-3.63)
N	244	244
Log likelihood	-21.91	-35.47
LR Chi2	2.05	7.230
Prob>Chi2	0.076	0.004

Note*:* Bootstrap standard errors are used to control heteroskedasticty
* p<0.10, ** p<0.05, *** p<0.01

These initial results for the innovation Probit model in Table 5.5, suggest that only EDUC (education) is strongly positively significantly related to innovation, confirming hypothesis H2, that absorptive capacity may stimulate innovation. All other independent variables are insignificant and are consequently dropped in the parsimonious model. However, we also observed a weak positively significant relationship between PP (perceived price) and innovation in the full model, suggesting that if the products are more welcomed by the market, a lower perceived (quality adjusted) price may be generated which may consequently restrain firms innovation.

Table 5.6 Probit Model for Collaboration

	Full model	Parsimonious
	3	4
R&D	0.344*	0.521***
	(1.83)	(3.11)
PAT	-0.00892	
	(-0.49)	
EDUC	3.773***	3.362***
	(3.70)	(3.80)
TL	0.00122	
	(0.92)	
TG	0.000676	0.000996**
	(1.14)	(2.08)
SE	-0.0818	
	(-0.53)	
MCON	-0.765	
	(-0.75)	
OPR	10.05	
	(1.59)	
CAST	0.524	
	(1.27)	
PP	-0.184	
	(-0.11)	
DIS	0.644	
	(1.22)	
REG	0.680	
	(1.05)	
Constant	-7.136***	-4.161***
	(-3.17)	(-4.53)
N	244	244
Log likelihood	-65.90	-69.34
LR Chi2	12.64	14.01
Prob>Chi2	0.000	0.000

Note*:* Bootstrap standard errors are used to control heteroskedasticty
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Similar to Table 5.5, model 3, see Table 5.6, is estimated including all independent variables and control variables, whilst model 4 is the parsimonious estimation with significant variables only. We found EDUC (education) and R&D in both models are positively significantly related to collaboration. This indicates that an increasing ratio of people with higher qualifications or more innovation inputs will encourage firms to collaborate more. It therefore confirms hypotheses H4 and H5 that increasing innovative ability or/and absorptive capacity may stimulate collaboration (although the effect of innovation output, PAT (patent), seems not significant).

On the other hand, we also observe that TG (technology gap) is significant at the 5% significance level and is positive and significant in the parsimonious model. This confirms hypothesis H6, indicating that increasing either the technology gap or the technology level may result in a higher catching up capacity and encourage firms to collaborate. This phenomenon however appears less significant in model 3. Again, a low p value for the LR test means that we cannot reject the validity of all models.

Table 5.7 OLS, Fixed and Random Effect Model for Collaboration Cost

	OLS		Fixed effect		Random effect	
	Full model 5	Parsimonious 6	Full model 7	Parsimonious 8	Full model 9	Parsimonious 10
R&D	0.0648***	0.0582***	0.0465*	0.0577*	0.0668***	0.0734***
	(3.04)	(3.36)	(1.93)	(1.82)	(4.42)	(5.15)
PAT	0.000423		-0.00740**	-0.00728*	-0.00303*	-0.00297*
	(0.17)		(-1.99)	(-1.79)	(-1.76)	(-1.72)
EDUC	0.148	0.158*	0.134		0.119*	0.115*
	(1.55)	(1.66)	(1.38)		(1.79)	(1.71)
TL	-0.000285*		-0.000220**	-0.000250**	-0.000268**	-0.000202**
	(-1.73)		(-2.15)	(-2.23)	(-2.42)	(-2.04)
TG	0.0000230		0.0000251*		0.0000246	
	(1.16)		(1.89)		(1.16)	
SE	0.0397		0.00830	0.0117*	0.0165	
	(1.19)		(1.11)	(1.71)	(1.35)	
MCON	-0.0750		-0.0375		-0.0473	
	(-1.10)		(-0.26)		(-0.57)	
OPR	-0.282		0.795	1.161*	0.420	
	(-0.55)		(1.57)	(1.66)	(0.97)	
CAST	0.0429	0.0437*	-0.0935**	-0.0950**	0.0183	
	(1.44)	(1.68)	(-2.09)	(-2.05)	(0.64)	
PP	-0.515***	-0.518***	-0.128		-0.263**	-0.218*
	(-3.35)	(-4.21)	(-1.02)		(-2.10)	(-1.88)
DIS	-0.0299		-0.423		-0.0680	-0.0679*
	(-0.85)		(-1.51)		(-1.57)	(-1.65)
REG	0.0267				0.0198	
	(0.70)				(0.37)	
Constant	-0.171	-0.185	0.712***	0.524**	-0.0469	0.0436
	(-1.17)	(-1.53)	(2.64)	(2.30)	(-0.34)	(1.35)
N	244	244	244	244	244	244
LL	6.911	1.636	202.3	191.3	45.90	43.18
F test	12.82	34.39	2.02	2.49		
LR test					77.98	84.29
P value	0.0000	0.0000	0.0338	0.0276	0.0000	0.0000
Test			7=9	8=10	7=9	8=10
Hausman			40.56	14.42	40.56	14.42
Prob>Chi2			0.0000	0.0024	0.0000	0.0024

Note: LL represents Log Likelihood
Robust standard errors are used to control heteroskedasticty in OLS and Fixed effect approach
Bootstrap standard errors are used to control heteroskedasticty in Random effect approach
* p<0.10, ** p<0.05, *** p<0.01

Table 5.7 provides the estimation result for CP (collaboration cost) using three different approaches - a pooled OLS model, a fixed effect model and a random effect model. As before, we present estimates using the full model and the parsimonious model. The variable REG (registration) was omitted by STATA in fixed effect models because of collinearity.

In terms of the significance of the independent variables (excluding controls), the results from the OLS model show that innovative ability has a positive and significant impact when innovative ability is measured by R&D in both model 5 and 6, whilst TL (technology level) is significant and negative in the full model but not in the parsimonious model while EDUC (education) is significant and positive in the parsimonious model but not in the full model. On the other hand, in terms of control variables, PP is significant (and negative) in both OLS models, whilst CAST (complementary assets) is significant (and positive) in model 6.

In the fixed effect model, R&D, PAT (patent), TL (technology level) and CAST (complementary assets) are all significant in both the full and parsimonious models. In particular, the latter three variables influence collaboration cost negatively, showing that increasing either innovation output, technology level, or transaction cost for enforcement purposes may lead to a decrease in the cost percentage the firm bears. Moreover, we also observe collaboration cost may be positively related to TG in model 7, while SE (spillover effect) and OPR (operational personnel ratio) have positive and significant impacts in model 8.

Similar to the fixed effect models, R&D, PAT (patent) and TL (technology level) are significant determinants of collaboration cost in the random effect models. In addition, however, we also found a slightly positive relationship between EDUC (education) and CP (collaboration cost), and a slightly negative relationship between PP (perceived price) and CP (collaboration cost) in both models 9 and 10. Since we found that the perceived price always moves negatively with product acceptability in Chapter 4, this result reveals that either increasing absorptive capacity or product acceptability may result in firms paying a greater proportion of collaboration costs. Moreover, we found that DIS (district) has a significant and slightly negative impact on collaboration cost in model 10, suggesting that firms locating at Qingshanhu District (the high-tech district) may pay a smaller proportion when they collaborate, though this phenomenon was not observed in the full random effect model or the other models using different approaches.

In STATA, the fixed effect and random effect approaches are tested in different ways. For the fixed effect models an F test is employed, whilst the random effect models are tested using a Lagrange Multiplier (LM) test. However, no matter which test statistics are used, our result shows all models are valid. In particular, as Wooldridge (2002) suggested, we employed a Hausman test to choose between the fixed effect model and the random effect model. We tested both the full and parsimonious models i.e. we separately compared fixed and random effect models using either all independent variables and control variables, or, as in the parsimonious models, only significant variables. Therefore, model 7 is compared with model 9, whilst model 8 is compared with model 10. The idea of the Hausman test is that the null hypothesis is that the random effect model is the preferred model with unique errors independent of the regressors. If they are exogenous, then we cannot reject the null hypothesis. Otherwise, we reject the null hypothesis and prefer the consistent fixed effect model. One problem is that the Hausman test assumes that the random effect model is always efficient. But when it is not, the

Hausman statistics may give an incorrect outcome (Cameron, 2007). We thus employ a bootstrap Hausman test to tackle this problem.

The last row of Table 5.7 represents the result of this Hausman test. The small p value in the comparison in all models concludes that the fixed effect models (model 7 & 8) perform better.

5.5 Further Analysis

In this section, we further investigate the determination of innovation, collaboration and cost sharing by exploring timing and dynamic issues building on the initial analysis in section 5.4. Using Probit estimation, we first estimate models incorporating all of the independent and control variables with time dummy variables, and then compare them with parsimonious models. Due to the involvement of time, only firms with observations for all three sample years may be considered, which means we use a balanced sample, the general properties of which has been explored in Chapter 4.

5.5.1 Further Investigation on Timing Issue

To investigate whether the determinants of firms' innovative strategy varies with time, we estimate Probit models with time dummies for the binary dependent variables, COLL (collaboration) and INNO (innovation), whilst on the other hand, we build a two-way fixed effect model with time dummies for the continuous dependent variable CP (collaboration cost). Their structures are as follows:

$$\Pr(Y_{it} = 1 | X_{it}) = \Pr(X_{it}^{'}\beta + \gamma_t + \varepsilon_i > 0)$$
$$Y_{it} = X_{it}^{'}\beta + \alpha + \gamma_t + u_i + \varepsilon_{it}$$

where γ_t is the time dummy. Taking time dummy variables into account may allow us to consider both unobserved time-variant specific influences and entity-variant specific influences. This idea is even more emphasised in the two-way fixed effect model (Baltagi et al, 2001). To avoid the dummy variable trap, we propose introducing only two time dummy variables - one for observations in year 2006 and one for year 2007. Table 5.8-5.10 are the estimation results for innovation, collaboration and collaboration cost, respectively. To control for potential heteroskedasticty, we employ bootstrap standard errors in all probit models and robust standard error in both OLS and two-way fixed effect models.

Table 5.8 Probit model with Time Dummies for Innovation

	Full model 11	Parsimonious 12
PAT	11.68	
	(0.00)	
EDUC	8.399***	10.51***
	(1.51)	(3.41)
TG	-0.0000550	
	(-0.04)	
SE	5.192	
	(0.00)	
MCON	0.948	
	(0.30)	
OPR	24.48	39.41*
	(0.77)	(1.92)
CAST	-0.248	
	(-0.19)	
PP	11.26	
	(1.24)	
DIS	0.182	
	(0.14)	
REG	0.993	
	(0.53)	
2006.Time	-0.461	-0.422
	(-0.42)	(-0.49)
2007.Time	-0.811	-0.767
	(-0.51)	(-0.77)
Constant	-3.905	-3.438***
	(-0.70)	(-3.46)
N	192	192
Log likelihood	-16.26	-21.99
LR Chi2	2.555	7.819
Prob>Chi2	0.055	0.003

Note: Bootstrap standard errors are used to control heteroskedasticty
* p<0.10, ** p<0.05, *** p<0.01

We estimate using all the independent variables, control variables and time dummies in model 11, and then, following the parsimonious approach, we use only the independent variables which are significant in model 12. In general, the results are similar to those in in Table 5.5. Only EDUC (education) is significant (and positive) in both the models, confirming H2, that increasing absorptive capacity may stimulate technology change. In addition, different from the Probit model without time dummies, we found that OPR (operational personnel ratio) is also significant and impacts positively on innovation in model 12, indicating that increasing safeguards in transaction costs may also encourage innovation. However, on the other hand, since none of the time dummy variables is significant throughout all three models, we did not find any evidence that shows that time affects firms' innovative decisions.

Similar results can be seen in the estimates of the Probit model of collaboration. EDUC (education) is positively related to collaboration. However, by comparing with Table 5.6, we found that, after allowing for time dummies, R&D in model 13 and TG (technology gap) in model 14 are no longer significant. Instead, we observe that CAST (complementary assets) impacts significantly and positively on COLL (collaboration) in the parsimonious model. Together with the positive and significant variable EDUC (education) and R&D, model 14 indicates that increasing either R&D expenditures, or employees with higher education backgrounds, or transaction cost from an enforcement purpose, may stimulate collaboration. On the other hand, again, as no time dummy is statistical significant, we do not observe any time effect on collaboration.

Table 5.9 Probit Model with Time Dummies for Collaboration

	Full model	Parsimonious
	13	14
R&D	0.260	0.396**
	(1.30)	(2.41)
PAT	-0.00822	
	(-0.46)	
EDUC	3.638***	3.237***
	(3.68)	(3.87)
TL	0.000875	
	(0.67)	
TG	0.000399	
	(0.70)	
SE	-0.0752	
	(-0.51)	
MCON	-0.862	
	(-0.77)	
OPR	10.32	
	(1.51)	
CAST	0.729	0.701*
	(1.59)	(1.91)
PP	0.619	
	(0.34)	
DIS	0.412	
	(0.80)	
REG	0.0732	
	(0.11)	
2006.Time	-0.0989	-0.0269
	(-0.25)	(-0.07)
2007.Time	0.277	0.446
	(0.70)	(1.21)
Constant	-7.168***	-6.799***
	(-3.09)	(-3.28)
N	192	192
Log likelihood	-59.75	-62.73
LR Chi2	9.840	10.78
Prob>Chi2	0.001	0.001

Note*:* Bootstrap standard errors are used to control heteroskedasticty
* p<0.10, ** p<0.05, *** p<0.01

Table 5.10 Two-way Fixed Effect Model for Collaboration Cost

	OLS		Two-way fixed effect	
	Full model	Parsimonious	Full model	Parsimonious
	15	16	17	18
R&D	0.0690***	0.0894***	0.0493*	0.0757**
	(2.79)	(10.35)	(1.67)	(2.17)
PAT	0.000101		-0.00754**	-0.00733*
	(0.04)		(-2.16)	(-1.87)
EDUC	0.142		0.158	
	(1.32)		(1.55)	
TL	-0.000266		-0.000217*	-0.000225*
	(-1.48)		(-1.77)	(-1.92)
TG	0.0000247		0.0000352**	0.0000236**
	(1.04)		(2.23)	(2.08)
SE	0.0346		0.00790	
	(1.02)		(0.96)	
MCON	-0.106		-0.0194	
	(-1.05)		(-0.11)	
OPR	-0.234		0.760	
	(-0.38)		(1.19)	
CAST	0.0607		-0.112**	-0.124**
	(1.38)		(-2.14)	(-2.14)
PP	-0.543***	-0.539***	-0.145	
	(-2.94)	(-3.85)	(-1.11)	

DIS	-0.0355		-0.422	
	(-0.82)		(-1.44)	
REG	0.0227			
	(0.48)			
2006.Time	0.00727	0.00360	0.00833	-0.00914
	(0.16)	(0.08)	(0.32)	(-0.32)
2007.Time	-0.0412	-0.0435	-0.0294	-0.0359
	(-0.84)	(-0.88)	(-1.26)	(-1.42)
Constant	-0.237	0.0410	0.807**	0.687**
	(-1.12)	(1.38)	(2.53)	(2.38)
N	192	192	192	192
rho			0.846	0.789
F test	10.34	27.05	2.135	2.172
Prob>F	0.0000	0.0000	0.0487	0.0237

Note*:* Robust standard errors are used to control heteroskedasticty for both OLS and Two-way fixed effect approaches

* p<0.10, ** p<0.05, *** p<0.01

Table 5.10 contains the comparison between the OLS model of collaboration cost with time dummies and the two-way fixed effect model with time dummies. Similar to the standard fixed effect model in Table 5.7, REG (registration) was omitted in two-way fixed effect estimation because of multi-collinearity. The results show that different implications may be drawn from the two approaches.

In estimates 15 and 16, similar to OLS estimation in Table 5.7, R&D, and PP (perceived price) are significant in the full model and the parsimonious model. However, with the time dummies added, the variables EDUC (education), TL (technology gap) and CAST (complementary assets) are no longer significant in OLS estimation. In two-way fixed effect model, we found R&D, TG (technology gap), PAT (patent), TL (technology level), and CAST (complementary assets) all impact significantly on CP (collaboration cost) in both models 17 and 18. In particular, the first two independent variables influence collaboration cost positively, whilst the other three variables tend to influence the CP (collaboration cost) negatively. Also, neither the 2006 time dummy nor the 2007 time dummy are significant , which indicates that no time effects are to be detected. The F statistics indicates the null hypothesis that all the variables' coefficients equal to zero may be rejected.

5.5.2 Further Investigation on Dynamics Issue

In this sub-section, we attempt to detect whether dynamic issues play an important role in firms' technology change decisions. To achieve this goal, information relating to prior time periods must be included as regressors. However, since there are only three time periods in our dataset, two year lags will significantly reduce the number of observations, which will consequently dramatically decrease the credibility of the estimates. Following the suggestion of Jackle and Li (2006) who also employed three years micro panel to analyse the relationship between firm dynamics and institutional participation, we therefore construct a dynamic model by including a one year lagged dependent variable as a regressor. No other time variables are included in the dynamic models (they had not been significant previously anyway). On the other hand, evidence shows that identification of unit root in micro panel data requires at least four time periods, i.e. T>3, we may not test the stationarity of the balanced sample because of insufficient observations (Bond et al, 2005; Blander, 2012). Thus we have:

$$\Pr(Y_{it} = 1 | X_{it}) = \Pr(\gamma Y_{i,t-1} + X'_{it}\beta + \varepsilon_i > 0)$$
$$Y_{it} = \gamma Y_{i,t-1} + X'_{it}\beta + \alpha_i + \varepsilon_{it}$$

The first equation listed above is the Probit model with a one year lagged dependent variable which we estimated by using an ML estimator. The second is a dynamic panel data model (DPD) with a one year lagged dependent variable which is estimated by the Blundell-Bond estimator, which is more efficient than Arellano-Bond estimator in a case of small sample (Bond, 2002).

To control for any heteroskedasticty, we employ bootstrap standard errors for all the Probit models and the GMM approach for the dynamic panel model, which also controls for endogeneity problems by using instrumental variables and autoregression problems via lagged independent and control variables (Holtz-Eakin et al, 1988).

Table 5.11—5.13 report the regression results with lagged dependent variables included for innovation, collaboration and collaboration cost respectively. We first investigate the lagged dependent variable's impact together with independent variables and controls. Following the parsimonious approach, we then extract the significant independent variables and re-estimate by using only them with a lagged dependent variable.

Table 5.11 Dynamic Probit Model for Innovation

	Full model 19	Parsimonious 20
L.INNO	20.44**	12.22**
	(1.14)	(2.48)
PAT	10.4	
	(2.82)	
EDUC	20.76***	20.61***
	(1.18)	(4.38)
TG	0.00911	
	(0.88)	
SE	4.828	
	(0.00)	
MCON	-26.65	
	(-0.90)	
OPR	150.3	107.3***
	(1.38)	(2.84)
CAST	2.247	
	(0.46)	
PP	1.142	
	(0.14)	
DIS	-4.869	
	(-1.02)	
REG	-4.281	
	(-0.60)	
Constant	-20.56	-13.00***
	(-0.77)	(-5.99)
N	128	128
Log likelihood	-5.212	-9.948
LR Chi2	1.788	2.724
Prob>Chi2	0.091	0.049

Note*:* Bootstrap standard errors are used to control heteroskedasticty
* p<0.10, ** p<0.05, *** p<0.01

Different from the initial analysis of the Probit model, the results in Table 5.11 shows that EDUC (education) is significantly (positively) related to innovation for both estimates. We also observe that OPR (operational personnel ratio) in model 20 is significantly and positively related to innovation. More importantly, lagged INNO (innovation) is significant and positive in both the full model and the Parsimonious model, suggesting that firms that have previously innovated also tend to innovate in the present.

Table 5.12 Dynamic Probit Model for Collaboration

	Full model 21	Parsimonious 22
L.COLL	1.460** (2.49)	1.450*** (3.02)
R&D	0.242 (0.92)	
PAT	0.00701 (0.27)	
EDUC	3.486** (2.13)	3.757*** (2.75)
TL	0.00258 (0.94)	0.00389 (1.61)
TG	0.000516 (0.73)	
SE	-0.511 (-1.06)	-0.565 (-1.34)
MCON	-1.428 (-0.86)	
OPR	8.448 (1.02)	12.33* (1.66)
CAST	0.460 (0.72)	
PP	3.861 (0.90)	
DIS	-0.228 (-0.35)	
REG	-0.747 (-0.87)	
Constant	-5.346* (-1.69)	-3.227*** (-3.15)
N	128	128
Log likelihood	-33.81	-36.53
LR Chi2	1.752	1.922
Prob>Chi2	0.093	0.083

Note*:* Bootstrap standard errors are used to control heteroskedasticty
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The very low p value on lagged COLL in Table 5.12 suggests similarly that firms that have collaborated in the past also collaborate in the present. Another variable that significantly influences the collaboration decision is EDUC, indicating that higher absorptive capacity may stimulate collaboration. Last but not least, the variable OPR (the operational personnel ratio) is slightly positively significant in the parsimonious model.

Table 5.13 Blundell–Bond Dynamic Panel Data Model for Collaboration Cost

	Full model 23	Parsimonious 24
L.CP	0.380*** (2.74)	0.409*** (2.84)
R&D	0.0842** (2.33)	0.0664* (1.90)
PAT	-0.00663** (-2.36)	-0.00511** (-2.20)
EDUC	0.114 (0.88)	0.249** (2.03)
TL	-0.0000336 (-0.09)	-0.000180 (-1.27)
TG	0.0000224 (0.63)	
SE	-0.0203 (-0.35)	
MCON	0.0866 (0.35)	
OPR	-0.653 (-0.68)	
CAST	-0.00542 (-0.06)	
PP	-0.436* (-1.86)	-0.255 (-1.42)
DIS	-0.0202 (-0.19)	
REG	0.146 (1.09)	0.325** (2.18)
Constant	-0.171 (-0.36)	-0.102 (-1.31)
N	128	128
Wald Chi2	43.79	28.83
Prob>Chi2	0.000	0.000

Note*:* GMM standard errors are used to control heteroskedasticty
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5.13 explores how firms' collaboration cost percentage varies when we take lagged CP into account. Sargan tests in both the models are insignificant, indicating that there are no over-identification problems. We notice that either increasing R&D or decreasing PAT (patent) may result in a higher collaboration cost percentage when firms collaborate. Also as EDUC is significant and positive in the parsimonious dynamic models, this implies that firms with more highly educated employees may pay a larger share of collaboration costs. We also see a negative relationship between PP (perceived price) and CP in model 23, but a positive connection between REG (registration) and CP in model 24. The former relationship indicates that the more the product is welcomed by the market, the more is the cost paid by firms, whilst the latter result reveals that firms with domestic ownership may pay a higher cost percentage in collaboration. This may be partly because, comparing with foreign firms, efficiency in domestic firms is relatively low. The other reason might be an asymmetric distribution of technological capabilities (Kroll & Schiller, 2010). Rather than collaborating in R&D, the most common form of collaboration in local Chinese firms is adoption and adaption of new technology acquired from the collaboration partner (technology leader). As Webber (2005) stated, *'R&D is used to refer to the production of additional generic products particularly for China'.* Therefore the real role of the collaborator in Chinese local firms is as a copier and as a result takes more responsibility for costs. Both reasons may result in positive relationship between firms' domestic ownership and the collaboration cost percentage.

5.6 Conclusions

The purpose of this chapter is to explore the determinants of innovation, collaboration and collaboration cost via the analysis of data on innovation patterns in Chinese manufacturing industry initially explored in Chapter 4. This is the first academic attempt to undertake an empirical analysis of the determinants of collaboration and innovation using Manufacturing panel data in Nan Chang a mid-income region in a developing country.

It is also, to the best of our knowledge, the first work to empirically explore cost sharing strategies in technological collaborations. Some past studies have focused on the theory of cost sharing strategy in collaboration

(Combs, 1992), whilst others have emphasised cost allocation in non-technological collaborations (Bolton et al, 2005). Yet most studies looked at the determinants of gross collaboration cost, rather than the cost sharing issue. White and Steven (2005), for instance, illustrated a framework by investigating 231 contractual alliances between architects and general contractors. Their results suggest that the total value of collaboration cost may be influenced by task complexity, interpartner diversity, opportunism threats, and perceived equity. Our analysis differs from all of these. Our research, in this sense, not only is the first exploration on the innovation patterns through a panel of Manufacturing data in Nan Chang, but also contributes collaboration cost hypotheses to fill the gap of existing literature.

Since some of the basic assumptions of the game theory model developed above do not really match the nature of our test bed, rather than testing predictions generated directly from Chapter 3, we proposed a number of testable hypotheses generated from existing literatures and initial data exploration. We argue that three factors, innovative ability, absorptive capacity and catching up capacity, (in turn represented by R&D & PAT (patent), EDUC (education), and TL (technology level) & TG (technology gap) respectively) are positively related to the extent of innovation and collaboration.

Since collaboration cost shares depend upon collaboration occurring which in turn depends upon innovation occurring, to avoid selection bias, we firstly employed a general Heckman selection model and a Heckman Probit sample selection model respectively to explore if there might be sample selection bias in our estimates. The results from Table 5.3—5.5 show that no such selection bias is apparent in the estimates of all models, and thus we have proceeded by setting aside such problems and estimated models for each dependent variable individually.

Secondly, we establish a set of pooled panel models for initial analysis. In particular, we employ Probit models for both binary choice variables, innovation and collaboration, whilst we use OLS and both fixed effect and random effect models for the continuous variable collaboration cost. Adopting a parsimonious approach, we first estimate full models incorporating all independent variables together with control variables and then drop the least significant regressors, one by one, (on the condition that explanatory power of the regression is not significantly reduced), to achieve a parsimonious model with the fewest possible variables. To deal with heteroskedasticty, all standard errors are controlled by computation of bootstrap estimates in the Probit models and random effect models, or robust standard errors for OLS models and fixed effect models.

The main result from the initial analysis is that EDUC (education) is significantly positively related to both innovation and collaboration, indicating a positive relationship between absorptive capacity and technology change decisions. In addition, increasing TG (technology gap) and R&D may also slightly encourage firms to collaborate. In terms of collaboration cost sharing determinants, on one hand, the results from the fixed effect models reveal that higher innovation input, or lower innovation output, technology level, and complementary assets, may stimulate collaboration cost. On the other hand, in addition to those factors found significant in the fixed effect model, the random effect model also suggests that higher absorptive capacity or higher product acceptability may also encourage firms to carry a higher proportion of collaboration costs.

Further investigation of timing issues and dynamics were then undertaken by adding time dummies for the years 2006 and 2007 into both the binary Probit models for innovation and collaboration, and the OLS and two-way fixed effect models for collaboration cost. As in the initial analysis, bootstrap and robust standard errors are introduced to deal with heteroskedasticty. The results from Table 5.8—5.10 show that there is no significant time effect observed. We therefore may conclude that any unobserved characteristics may be time-invariant. To explore dynamic issues further we also considered a one time period auto regression (in the Probit model with bootstrap standard error and in the dynamic panel model with GMM standard errors). Due to the comparatively small size of our sample, we introduced just a simple one year lagged dependent variable as regressor in the models to explore if firms' past decisions affect their current decisions. The results in Table5.11—5.13 illustrate that for each of the three dependent variables past decisions matter i.e. Innovation (or collaboration, or a higher collaboration cost percentage) in the past, leads to innovation in the present (or collaboration, or a higher collaboration cost percentage).

Table 5.14 lists the estimation results for each independent variable as the response to the hypotheses table (Table 5.2) illustrated in the beginning of this Chapter. For hypotheses H1 to H3, only EDUC (education) is positively significant to INNO (innovation). The rest of the independent variables are all insignificant in all the parsimonious models. This finding seems to violate the partial correlation results in Chapter 4 (Table 4.10), which suggests R&D, PAT (patent), EDUC (education) and TL (technology level) all significantly impact on innovative decisions. However, since the variable R&D may not be truly exogenous, we actually exclude it from the models estimated here so that any impact of R&D on innovation still remains invisible.

In contrast, we did not observe any close partial correlation between R&D and COLL (collaboration), or between TG and COLL in either the unbalanced sample or balanced sample in Chapter 4 (Table 4.10). But from the econometric analysis both are positively related to the decision to collaborate. This indicates that increasing R&D, or employees with a higher education background, or the technology gap between technological leader and follower, could stimulate firms to collaborate.

In terms of the six hypotheses, on the basis of the sample data analysed, we may state that only H2, H4, H5, and H6 are not rejected by the results of our models. However, although only absorptive capacity appears to be crucial for innovation, innovative ability, absorptive capacity and catching up capacity are all important to collaboration. This may explain why nearly 50% of the innovative projects are collaborative projects (Table 4.6 in Chapter 4).

Table 5.14 Results of Testable Hypotheses

		INNO		
			Not rejected	Rejected
R&D	Innovative ability	H1: +		
PAT				
EDUC	Absorptive capacity	H2: +	1 2 11 12 19 20	
TL	Catching up capacity	H3: +		
TG				
		COLL		
			Not rejected	Rejected
R&D	Innovative ability	H4: +	3 4 14	
PAT				
EDUC	Absorptive capacity	H5: +	3 4 13 14 21 22	
TL	Catching up capacity			
TG		H6: +	4	

The regression results summarised in Table 5.15 are intended to provide further detail upon the determinants of collaboration cost sharing. As this appears to be the first time that the determinants of collaboration cost allocation have been explored empirically, we cannot generate any testable hypothesis from the prior literature. We hence rely upon the significant patterns that we have seen in the data rather than upon past theories or studies. These patterns have led us to propose that the collaboration cost percentage paid by firms:

H7: may go with the proportion of cost paid in previous collaborations
H8: may increase with R&D
H9: may increase with the ratio of employees with higher education.
H10: may increase with technology gap.
H11: may decrease with transaction cost (from an enforcement perspective).
H12: may decrease if the firm holds patents.
H13: may decrease with the firm's technology level.
H14: may decrease with the firm's perceived price.

Whether these hypotheses are rejected or not rejected is summarised in Table 5.15

Table 5.15 Other Results upon Dependent Variables

		CP	
		Not rejected	Rejected
Lagged CP	+	23 24	
R&D	+	5—10 15 18 23 24	
EDUC	+	6 9 10 24	
TG	+	7 17 18	
OPR	+	8	
SE	+	8	
REG	--	24	
CAST	--	7 8 18	6
DIS	--	10	
PAT	--	7—10 17 18 23 24	
TL	--	5 7—10 17 18	
PP	--	5 6 9 10 15 16 23	
		COLL	
		Not rejected	Rejected
Lagged COLL	+	21 22	
OPR	+	22	
CAST	+	14	
		INNO	
		Not rejected	Rejected
Lagged INNO	+	19 20	
OPR	+	12 20	
PP	+	1	

Table 5.15 also summarises other results re COLL and INNO i.e.

H15: Firms that have collaborated in the past may have more chance of collaborating in the present.
H16: Firms that have innovated in the past may have more chance of innovating in the present.
H17: The likelihood of a firm innovating is positively related to transaction costs from a monitoring perspective.

On one hand, H15 may be explained in terms of trust. Hill (1990) advocated that building trust and reputation between partners may sometimes make collaboration preferable to competition. Since one of determinants of trust would be related to past experience, the history of collaboration in the past must increase trust, which consequently encourages collaboration in the future (White, 2005). On the other hand, we found the result of H16 that more innovation in the past may lead to more innovation in the present contradicts with the 'two-cycle model' which suggested that foreseen increase in research in the next period discourages research during the current period (Aghion & Howitt, 1992). This may happen as the escape effect in our test bed outweighs the Schumpeterian effect, so that firms try to keep innovating to obtain the 'abnormal payoff' earned by the technology leader (Aghion et al, 2005).

To explain the deduction behind H17 that a positive relationship exists between transaction cost and innovation, we may look into the relationship between transaction cost and collaboration, because collaboration is an important component of innovation. As discussed in Chapter 2, Williamson (1985) and Hill (1990) advocate that the transaction cost on one hand must help firms to secure their collaborative return so that it may increase the success rate of collaboration, whilst on the other hand, it also increases the burden of cost, which decreases firms' net profit in the post collaboration period. Therefore, the relationship between transaction cost and collaboration generally depends upon the joint effect of balancing opportunism reduction and cost saving. Our result from the set of econometric models indicates a slightly positive relationship between collaboration and transaction cost. For instance, model 22 confirms a significant and positive relationship between collaboration and OPR (transaction cost from the monitor perspective) whilst model 14 suggests a significant and positive relationship between collaboration and CAST (transaction cost from an enforcement perspective). These results jointly reflect that in our case, when transaction cost increases, the effect of opportunism reduction overweighs the effect of cost saving in collaboration. Thus we see a positive relationship between transaction cost and collaboration, which consequently results in a positive relationship between collaboration cost and innovation. We believe that if we were able to increase the sample size thereby allowing the use of more sophisticated models including more control variables, the positive relationship between transaction cost and collaboration may prove to be even more significant.

Apart from hypotheses H15—H17, we did not find any impacts of other control variables on innovation or collaboration from the second and the third part of Table 5.15. Evidence shows no significant relationship has been found between DIS and innovation (collaboration), or REG and innovation (collaboration), indicating that, whether firms locate at Qingshanhu District (high-tech district) or whether the firm is domestically owned, do not influence innovation or collaboration decisions. This indicates that across firms in Nan Chang the pattern of innovation is equally distributed in different regions and across different ownership.

Particularly interestingly, we did not find a significant relationship between SE (spillover effect) and innovation or collaboration, suggesting that the chance of imitation does not affect innovation or collaboration. This result looks very similar to the prediction 15 and 16 derived from the game theory chapter (Table 3.10, Figure 3.21 to Figure 3.28). As we mentioned in Chapter 3, the reason may be partly because the net payoff from collaboration or innovation must far outweigh the gains from imitation. Therefore for firms who decide to choose innovation or collaboration, tighter or looser IPR does not dramatically influence their technological strategies. On the other hand, it may be because shortage of capacity restricts innovation or collaboration so that in practice, innovation or collaboration is not actually a choice for them. It might also be that other factors such as limited patent history, few employees with higher education background, a low technology level or being far behind the technological leader may all deter innovating or collaborating before SE even comes into play.

Although we have found quite a rich set of results it should be noted that there are limitation in this analysis. The most obvious is the small size of data sample, although there are now techniques that help overcome this limitation (Jackle & Li, 2006). Even so, since data with less than four time periods do not allow us to run unit root test, we may not further explore the stationarity of our sample (Bond et al, 2005; Blander, 2012). One cannot predict what impact a larger sample would have but there is the possibility that more variables may be significant or a more detailed exploration may be undertaken (especially of dynamics). Apart from possible unobserved variables, as we discussed before, more sophisticated models which emphasise time series effects may become feasible as may large sample techniques such as ARIMA models, and GARCH models.

6 Conclusions

6.1 Overview

This thesis was motivated in part by the relatively limited emphasis placed upon collaboration (as opposed to competition) in innovation in economics literatures. In particular, to the best of our knowledge, there has been little discussion of collaboration using game theoretic models which incorporate product innovation rather than process innovation, and consider both transaction cost theory and intellectual property rights protection. We believe that reality is better reflected in models which incorporate product innovation, and allow imitation and inter firm technological collaboration. In addition, to the best of our knowledge, there has been no discussion in the literature of the determinants of collaboration and collaboration cost allocation at firm level in China. These findings from the literature review jointly lead us to consider: under what circumstances firms will collaborate in a competitive market; what will be the cost sharing strategy when collaboration occurs; what can we discover of collaboration patterns in the Chinese manufacturing industry.

To fulfil our research purpose, in Chapter 3, we develop a game theoretic model based on Vickers (1986) but (i) taking collaboration and imitation into account and (ii) also considering product innovation instead of process innovation. For the sake of simplicity, we first investigated collaboration when the firm faces a three-strategy set (collaboration, innovation, do nothing), and then a four-strategy set (collaboration, innovation, imitation, do nothing). In each case, by looking at the various possibilities and their different collaboration incentives, we generated a table and a decision map that summarises the best equilibrium innovation strategy given different market characteristics and the conditions that will determine whether or not a firm will collaborate. In particular, we distinguish by different market types i.e. whether the market is a persistent dominance market or action reaction market.

To investigate further the collaboration equilibrium, we used an example employing a utility function proposed by Shaked and Sutton (1990) with a modified perceived price function suggested by Matsubayashi (2007). In this model consumers obtain more utility from goods with higher technology but same price. Since the improved utility function contains both a product substitution index which reflects the technological differentiation of products, and perceived price, which in turn reflects the feedback from process technology embedded in products, the new utility function we employed covers both production cost and consumer preference. Besides, since the cost function for changing the technology associated with products includes a spillover index and transaction costs, it allows us to accurately calculate and compare the incentives of adopting different strategies. Compared to models used in previous studies we consider that this approach reflects the real world more effectively.

To solve for the collaboration equilibrium in the illustrative examples, we calculated the Cournot equilibrium by backward induction, allowing the market leader to make decisions, taking into account the reactions of his rival. Consequently, the collaboration incentive, innovation incentive and imitation incentive can all be precisely stated. If firms collaborate, we assume the market reaches equilibrium only when firms' joint payoff is maximised. Under this condition, the findings suggest that the collaboration cost paid by the market follower is determined by three sub-equations and may vary with market characteristics. To understand this better, we extended the collaboration condition tables and the collaboration cost condition tables by substituting the incentives of different strategies and generated various predictions as to how the possibility of collaboration and its corresponding cost change with different market characteristics. In addition, we also used a MATLAB animation programme to show to what extent imitation affects collaboration opportunity and the collaboration cost paid by the technology follower (predictions 14—16 in Table 3.10).

Looking at the impact of changing model parameters in both the collaboration cost equation and the collaboration incentive equation, a number of findings are drawn from the theoretical models. We classified the resulting 18 predictions into three groups, which respectively concern 'collaboration probability', 'collaboration cost' and 'other issues' (Table 3.10). In particular, the majority of the predictions in the first two groups relating to collaboration probabilities and collaboration cost are new to the existing literatures.

Table 3.10 Generated Predictions

Predictions	Keynotes of each Prediction
	Predictions about the Probability of Collaboration
3	In a three-strategy persistent dominance market, the probability of collaboration generally increases with the product substitution index, the initial technology level and the discount rate of price sensitiveness, but decreases with the technology gap.
5	In a three-strategy action reaction market, the probability of collaboration generally increases with the initial technology level, but decreases with the technology gap, the product substitution index and the discount rate of price sensitiveness.
13	In a four-strategy persistent dominance market, where the transaction cost is low, adding the option of imitation would decrease the probability of collaboration when the product substitution index is high or the initial technology level is low, where firms in both situations may prefer to imitate rather than collaborate.
14	In a four-strategy persistent dominance market, where transaction cost is low, increasing the size of imitation will further decrease the collaboration opportunity when the product substitution index is high or the initial technology level is low.
15	In a four-strategy persistent dominance market, where transaction cost is high, increasing the size of imitation will neither stimulate nor decrease the collaboration opportunity.
16	In a four-strategy action reaction market, the probability of collaboration by firms does not differ from when imitation is feasible.
4	Regardless of whether there are three or four strategies, in a persistent dominance market,

	increasing transaction costs will stimulate collaboration until the transaction cost reaches a certain level. When transaction cost is over that level, the chance of collaboration will not be affected by further increases in transaction costs.
6	Regardless of whether there are three or four strategies, in an action reaction market, increasing transaction cost neither encourages nor diminishes the probability of collaboration.
	Predictions about Collaboration Cost
9	In a three-strategy persistent dominance market, the collaboration cost percentage paid by the lower technology firm generally increases with the discount rate of price sensitiveness, but decreases with increases in the technology gap, the product substitution index and the initial technology level. However in a market with highly similar products, the collaboration cost percentage paid by the lower technology firm increases with the product substitution index.
10	Under a three-strategy persistent dominance market structure, if firms collaborate, the firm with the lower technology level must pay. As to the percentage he pays, this depends upon the nature and market structure of both firms. However, in rare cases, the percentage could exceed 100%.
11	In a three-strategy action reaction market, the collaboration cost percentage paid by the lower technology firm generally increases with the technology gap and the initial technology level, but slightly decreases with increases in the product substitution index and the discount rate of price sensitiveness.
12	In a three-strategy action reaction market, if firms collaborate, the firm with the lower technology level must pay more than 50% of the R&D cost.
17	In a four-strategy persistent dominance market, (different from the three-strategy case), the collaboration cost portion paid by the lower technology firm will never exceed 100%.
18	There are generally no significant differences between the collaboration cost equilibrium in the four-strategy case and the three-strategy case. However imitation may induce a lower collaboration cost share for firm L if there is a small technology gap.
	Predictions about Other Issues
1	Increases in the rival's product technology level and market size or decreases in the market structure coefficient, will decrease the firm's price, output and revenue.
2	Increasing the firm's own technology level must increase its price level and revenue (which reflects the theory of creative destruction).
7	Increasing the value of α may cause the market structure to change from persistent dominance to action-reaction.
8	When α is small, neither firm will wish to collaborate even though they have the chance to do so. Firms will collaborate only when α is above a certain level.

Chapter 4 introduced the data. The data employed are derived from the China Innovation Survey and the Annual Corporate Financial Survey undertaken by the National Bureau of Statistics of China, covering Large and Medium sized enterprises in 33 industries in manufacturing. Restrictions on the use of panel data imposed by the Statistics Law of the Peoples' Republic of China, has limited the extent to which the data that are employed here have been used in the past. To the best of our knowledge, this thesis is the first to attempt to analyse collaboration strategy at firm level in China (and in fact in any mid-income level in a developing country). In particular, we chose to cooperate with the Nan Chang Statistics Department in order to have full access to the two confidential surveys above in Nan Chang from 2005 to 2007.

However, it is not easy to transform the game theoretic predictions into testable hypotheses for empirical work. One reason is that the Chinese market is not a market economy where firm ownership simply belongs to private individuals or shareholders. The data for the Chinese region studied reveals that most collaboration activities have been between firms and local government (Table 4.6). This indicates that in contrast to the assumption of the game theory model that collaboration only occurs between firms, collaboration observed from our data may also be associated with non-competing players, such as institutions, universities, or even local government. In addition, for example, it is not possible using the data: to separate out the high cost firm from the low cost firm; an action reaction market from a persistent dominance market; product innovation from process innovation; or three and four-strategy situations.

Therefore, rather than try and directly test the game theory predictions empirically, we decided to establish several other hypotheses which are testable using the empirical data available. In particular, following Castellacci (2008) and Blalock & Gertler (2009), we defined three factors which may potentially influence collaboration or innovation, which are the innovative ability, absorptive capacity, and catching up capability of firms. These three independent concepts were then measured by five independent variables (R&D, patent, education, technology level, and technology gap) respectively. In addition, we also defined various control variables as suggested by existing literatures and initial analysis of the data. These included market concentration, the operational personnel ratio, complementary assets, perceived price, district, and registration. In particular, the first three control variables jointly represent the effect of transaction cost from a negotiation perspective, monitoring perspective, and enforcement perspective, respectively. Via these three control variables, we therefore may explore the impact of transaction cost on different innovative strategies as well.

In the empirical work we found it useful to define innovation as encompassing both self-innovation and innovation via collaboration. This differs from the definition of innovation in the game theory model where innovation is assumed as self-innovation only.

We firstly summarised the economic environment in our sample area. Table 4.2 illustrates the comparison of main economic indicators, derived from local, provincial and national statistical yearbooks. The result shows that the sample region reflects a mid-income and moderately developed region with intensive growth potential. We then explore summary statistics relating to the indicators of innovation, collaboration and cost shares. We showed that nearly half of the firms in the sample chose innovation, whilst approximately 60% of the firms chose collaboration when they innovated. Also, in terms of ownership, we found that both domestic firms and assets of Hong Kong, Macao, Taiwan are innovative or collaborative (Table 4.7). Moreover, since 55% of the firms which innovate are located at Qingshanhu District and more than 72% of the innovative firms at Qingshanhu District chose collaboration, the result indicates that firms at the high-tech zone in Nan Chang are more likely to innovate or collaborate.

Next we looked at partial correlations between the three performance measures and the independent variables and control variables (see Tables

4.10). Besides, the partial correlations suggest a significant relationship between the three independent factors and the three dependent variables.

Six hypotheses related to the three dependent variables (‘collaboration cost’, ‘collaboration’ and ‘innovation’) and associated with the three identified factors (innovative ability, absorptive capacity, and catching up capability of firms) are tested more precisely in Chapter 5. Since the dependent variables, ‘collaboration’ and ‘innovation’ are both binary variables, there may be a bias in the estimates if we estimate without taking the sample selection process into account. To solve this problem, we first employed the general Heckman selection model and a Heckman Probit sample selection model respectively to detect whether there is any selection bias between collaboration cost and collaboration, and between collaboration and innovation. Since the results from both models did not reject the null hypothesis which assumes no selection bias, we proceeded by investigating each dependent variable individually.

In initial econometric analysis, we employed the Probit models for both innovation and collaboration, whilst OLS, a fixed effect model and a random effect model are employed for collaboration cost. In particular, by adopting a parsimonious approach, the estimate with fewest possible explanatory variables may be derived by dropping least significant variables from the full model containing all independent variables and control variables. In addition, time dummies and one period lagged dependent variables were added into individual models to investigate timing dynamic issues. In particular, we employed two-way fixed effect models and dynamic panel data models for analysing timing and dynamics of collaboration cost shares. To deal with heteroskedasticty, bootstrap estimates were computed for the Probit models and random effect models, whilst robust standard errors were calculated for OLS and fixed effect models (including the two-way fixed effect model), and the GMM standard error was investigated for the dynamic panel data model.

The results from Table 5.14 show that all three factors are significant to collaboration, whilst only absorptive capacity is significant to innovation. In addition, results from Table 5.15 reveal that there is no timing effect for all dependent variables, indicating all unobserved effect might be time-invariant. Also, we found that all one period lagged dependent variables have positive significant impacts on the relevant dependent variables, suggesting that the innovative (or collaborative) strategies adopted in the past may positively influence the innovative (or collaborative) strategies adopted in the present. All the significant hypotheses not rejected by the econometric models may be gathered together as follows:

H2: A firm with high absorptive capacity is more likely to innovate
H4: A firm with high innovative ability is more likely to collaborate
H5: A firm with high absorptive capacity is more likely to collaborate
H6: A firm with high catching capacity is more likely to collaborate.
H15: Firms that have collaborated in the past may have more chance of collaborating in the present.
H16: Firms that have innovated in the past may have more chance of innovating in the present.
H17: The likelihood of a firm innovating is positively related to transaction costs from a monitoring perspective.

Although the existing literature does not offer any testable hypotheses re collaboration cost, because, to the best our knowledge, this is the first attempt to explore empirically the cost sharing strategy in technological collaborations, we have explored whether the factors that affect innovation and collaboration also affect collaboration costs shares. After observing the patterns in the data we consider that we cannot reject the following hypotheses, that collaboration cost shares:

H7: increase with the proportion of costs paid in previous collaborations.
H8: increase with R&D.
H9: increase with the ratio of employees with higher education.
H10: increase with the technology gap.
H11: decrease with transaction cost (from an enforcement perspective).
H12: decrease if the firm holds patents.
H13: decrease with the firm’s technology level.
H14: decrease with the firm’s perceived price.

6.2 Implications

6.2.1 Implications from Results

This section is concerned with the implications of the thesis results and may be divided into three categories: theoretical implications, empirical implications and methodology implications. The first and second implications are mainly concerned with the connections between existing literatures and the main findings coming from our game theory model, and the econometric models, respectively, whilst the last, methodology implications, is about learning from the MATLAB programming used in this thesis.

Theoretical implications

The predictions of the game theory model summarised in Table 3.10 are generally concerned with two significant findings. The first is that collaboration opportunity and the collaboration cost paid by the technological follower may vary with market types and various market characteristics, including the extent of product substitution, the technology level, the technology gap, transaction costs, and the discount rate of price sensitiveness. The second is that the impact of alternative strategies (e.g. imitation) on collaboration and collaboration cost are not univariate. The effect may vary with the other market characteristics mentioned above.

Some of the impacts of market characteristics on collaboration which we derive from our theory have been found in previous studies. For instance, a negative relationship between product substitution and collaboration is generated by Yi (2007) who believes that more imitation must result in less collaboration and less R&D input but faster imitation, making it difficult for firms to differentiate themselves. However, Tan (2007) disagrees with this point of view, and suggests that when the product substitution index is relatively small, the possibility of collaboration may increase. Predictions 3 and 5 in our theory however, clarify these contradictory debates by supporting Yi (2007) and Tan (2007) for different market types.

A similar phenomenon may be found in the relationship between transaction cost and collaboration. Williamson (1985) and Hill (1990) argue that transaction costs reduce the opportunism embedded in the technology transaction process. Since a trade-off exists between the cost increment and opportunism reduction, there is a large amount of debate in the literature about the relationship between collaboration and transaction cost. Some believe the effect of higher transactions costs may outweigh the effect of opportunism reduction, indicating a negative relationship between collaboration and transaction cost (Brockhoff, 1992), whilst others may support the very opposite view (Heide & John, 1990). By introducing a transaction cost parameter in the utility function inspired by Shaked and Sutton (1990) and Matsubayashi (2007), our model, however explains this complex relationship upon different situations and different market types (Predictions 4 and 6). The results show that other various market characteristics may also influence the relationship between transaction cost and collaboration in a persistent dominance market.

Both these examples suggest that it may not be appropriate to conclude whether firms would collaborate or not by simply judging partial relationships between one particular market characteristic and collaboration. Similarly, the other finding from the game theory model suggests that the impact of the alternative strategy, imitation on collaboration is also not univariate. This implication supports the idea that the joint venture decision may depend upon spillover size, as proposed by Greenlee & Cassiman (1999) (although they concentrate on process innovation rather than product innovation).

Empirical implications

We observe a positive relationship between R&D and collaboration in the empirical results, which confirms the hypothesis that innovative ability positively affects collaborative decisions. This provides evidence for Motta (1992) who argues for a positive impact on cooperative agreements. It also supports the research outcome proposed by Zhang et al. (2007) who investigated the positive relationship between R&D intensity and international joint ventures (IJV). However, our empirical results do not seem to support a positive relationship between R&D and innovation. This is because as our measure of innovation indicates as any firm (or innovation project) must involve some R&D input, R&D may not truly be exogenous. We have therefore dropped this variable as an independent variable when we explore innovative ability in empirical models relating to innovation. It does not, however, necessarily mean that R&D has no significant impact on innovation.

The result of the game theory also points out a negative relationship between technology gap and collaboration. However, surprisingly, this prediction is not fully supported in the empirical studies, which reveal a positive relationship. As suggested by Verspagen (1991), this ambiguous relationship may be partly because on the one hand, larger technology gaps may stimulate firms to collaborate, whilst on the other hand, larger technology gaps may decrease the possibility of catching up. The relationship between technology gap and collaboration consequently depends upon the joint effect. Therefore, for large and medium firms at Nan Chang, the motivation of profit seeking from an increasing technology gap may outweigh the worries of being left behind. The other reason that may cause this result is, in contrast to the measures of the technology gap in empirical studies, the definition of technology gap in game theory assumes that collaboration can only occur between firms whereas we see many different types of collaboration. This assumption also affects the results re other relationships between technology gap and collaboration.

As the indicator of absorptive capacity, education appears strongly significant as a determinant of both innovative and collaborative decisions, providing evidence in support of the models proposed by Castellacci (2008) and Blalock & Gertler (2009). This is because, regardless of the pattern of technology change, increasing employees' education level may fundamentally increase the absorptive capacity, which is beneficial for technology diffusion. On the other hand, according to Klein and Lim (1997), compared with the importance of researchers, the positive impact of R&D is quite limited. To some extent, that may explain why innovative ability does not appear as a significant determinant of innovation.

Methodology implications

There are two reasons why we employed MATLAB programmes in the game theoretic chapter. One is to solve the complex equilibrium of collaboration opportunity and collaboration cost, whilst the other is to explore the dynamic impact of imitation on collaboration and collaboration cost. To the best of our knowledge, only limited research has employed MATLAB programming in game theory modelling. The implications derived from our MATLAB programme proves that the animation programme itself could effectively solve for the game equilibrium and help us observe the impact of market characteristics on collaboration and collaboration cost.

6.2.2 Implications for Future Research

Similar to the previous sections, our implications for future research may be divided into three categories: theoretical implications, empirical implications and methodology implications.

As we found that collaboration and imitation may play an important role in a firm’s innovation decisions, the first theoretical implication is that future research may focus more on multi-choice cooperative games rather than multi-stage competitive games. Since collaboration may effectively share the collaboration cost and technological dominant payoff between players, the decision equilibrium in a cooperative market may be significantly different from equilibrium in a non-cooperative market. However, our game theory model was inspired by Vickers (1986), who distinguishes the market only by either persistent dominance or action reaction. These concepts seem relatively restrained if we want to expand the cooperative game by adding more players, more stages or even more choices. In the handbook about cooperative game theory by Branzei et al (2005), they address several models for Crisp, Fuzzy, and multi-choice games. The first model is that players are free to choose if they cooperate with all other players, whilst the second one allows a player to choose cooperation in many different levels. The multi-choice model is the intermediate structure that allows players to participate in cooperation at limited levels with finite partners. However, since the general multi-choice model has not been employed on the investigation of technological collaboration issues, adding other strategic choices by using multi-choice cooperative games, such as outsourcing, may be considered as one possibility in the future.

The second theoretical implication from our game theory is that we may expend the structures of utility or cost function by adding more variables. In our model, variables such as the product substitution index, the initial technology level, the technology gap, and the discount rate of price sensitiveness are respectively investigated re both collaboration opportunity and collaboration cost issues. Other possibilities which may affect collaboration or collaboration cost are however excluded. Segerstrom (1991) considers innovation determinants by looking at different R&D types, whilst Girma et al (2008) investigate the relationship between innovation and foreign direct investment. Such potential variables relating to innovation activity could thus be considered as part of a potential future research agenda.

The empirical findings may also have policy implications at firm and national policy levels by showing the determinants of innovation, collaboration, and collaboration cost. For instance, since all of innovative ability, absorptive capacity, and catching up capacity play an important role in collaboration, policies that aim to increase either R&D, education benefits, firms' technology levels or technology gaps by introducing more competition, may stimulate firms to collaborate. In addition, the limited data obtained only reflects the situation in China. Future research encompassing other regions and countries may thus also be welcome.

As we employed MATLAB programmes to automatically solve the collaboration decision equations, using MATLAB simulations to generate game equilibria may be considered as the methodology implication of our work. In our game theory models, regardless of the market types, there are three different sub-equations for collaboration for the firms in three-strategy sets and four sub-equations for collaboration for the firms in the four-strategy sets. The number of decision equations could dramatically increase if we introduced more strategic choices or more players into models. This indicates that the process of equilibrium calculation may become extremely complex. In particular, in a dynamic market with various changeable market characteristics, obtaining the solution to equation sets may seem impossible. This is one main reason why so many cooperative games are still only at the theoretical level. Therefore, as we experienced in Chapter 3, to bring more complex conceptual models into practice, using MATLAB programmes might be one possible solution.

6.3 Contributions

In general, the contributions of this study may be divided into three categories: theory contributions which are mainly contributions to economic theory; empirical contributions which concern whether the results match or differ from the predictions in existing literatures; and the methodology contributions which concern the novelty of the methodology used in our models.

Theory contributions

The thesis contributes to the relevant literatures in several branches of economics including game theory, transaction cost theory and intellectual property rights theory.

Firstly, the thesis extends our understanding of the impacts of collaboration possibilities in dynamic game theory. There is already a rich array of research involving game theoretic models of concerning the relationship between innovation and imitation which may be found in the existing literatures; however, our game theory model is the first attempt to bring both collaboration and imitation into a dynamic market with product innovation. Different from Vickers (1986), we concentrate more on product innovation and the collaboration opportunities associated with the impacts of imitation and other market characteristics on the equilibrium outcomes. Most existing work only covers some of these points. For instance, Greenlee & Cassiman (1999) who investigated a model of whether research joint ventures and collusion occur under different levels of spillover effect, explored the relationship between imitation and collaboration, but ignored the impacts of various market characteristics, such as technology gap and technology level. Others, such as Motta (1992) by presenting a partial equilibrium model with vertical product differentiation, explored the impact of cooperative agreements on R&D but ignored the option of imitation.

Another important contribution to the existing game theory literature, may be the patterns and determinants of collaboration cost. There is very limited research focusing on technological collaboration cost sharing issues, in particular, there is no game theory model covering the collaboration cost sharing decision for technology followers. Most of the existing game theory literature allows that collaboration cost is one motivator of collaborative firms, but seldom discusses the determinants of collaboration cost. Although the implications from costly contracts theory proposed by Grossman and Hart (1986) suggest that purchasing residual rights may help firms control abnormal profits from integration which consequently influences the outcomes of profit allocation, it does not mention what factors may actually influence cost allocation when firms collaborate technologically. Therefore, how to allocate cost during collaboration and what the optimal collaboration cost sharing strategy is for low technology firms still remains unknown. The answers to these two questions are particularly important for firms in developing countries, such as China. Our model in Chapter 3 however filled this gap. By using MATLAB figures, we explicitly explored how collaboration cost varies with different market types and market characteristics.

The third contribution of our works to game theory is that by employing Cournot equilibrium, we concentrated on the impact of collaboration from a general perspective. Different from Vickers (1986) who employed Bertrand competition to explore how markets tend to impact upon firms' innovative decisions, our model allows us to stand back and investigates how firms' collaborative decisions differ with different markets. Therefore the Vickers model concentrates more on market level strategies, whilst our game theory model focuses more on individual firm level strategies. In particular, by showing firms' decision maps, we are able to observe how firms' innovative (collaborative) decisions alter as market type changes.

Our work also enriches the understanding of transaction cost theory. The results from the game theory reveal that the elasticity of collaboration opportunity with respect to transaction cost in a persistent dominance market is much greater than in an action reaction market. In addition, the empirical results in Table 5.15 indicate a positive significant relationship between transaction cost and collaboration (innovation). In particular, evidence shows that transaction costs from a monitoring perspective and enforcement perspective are especially effective in increasing collaboration. Therefore, both the game theory model and the empirical results enrich our understanding of transaction cost theory.

Finally, our thesis contributes to results re intellectual property rights (IPR) theory by revealing the dynamic impacts of imitation on collaboration and collaboration cost. When firms' exclusive IPR can be expropriated or the market explodes significantly, the markets may allow imitation. By designing a MATLAB animation programme in the game theory model, we clearly show how imitation affects the collaboration opportunity and collaboration cost percentage respectively. Apart from the methodological contribution of this animation, these two issues have not previously been investigated by either Vickers (1986) or other researchers. The results show that when IPR is looser, more imitation does not necessarily decrease the chance of collaboration. The outcome thus may depend upon transaction cost level in markets and different market types.

This consequently reveals that the relationship between IPR and collaboration may not be univariate.

Empirical contribution

The empirical contribution mainly comes from the empirical work using Chinese manufacturing data in Chapter 4 and Chapter 5.

Firstly, we have contributed, by using Nan Chang's firm level data derived from the China Innovation Survey and the Annual Corporate Financial Survey from 2005 to 2007, being the first to investigate technological collaboration in a mid-income level developing country. Due to the confidential nature of the data and the Statistics Law of the People's Republic of China, the work is the first to explore and present patterns of innovation and collaboration. As well as the general picture of the patterns and determinants of collaboration and innovation in Jiang Xi province, we were also able to detect and investigate the distribution of collaboration and innovation by observing the breakdown by different industries and time periods. In particular, in the initial analysis in Chapter 4, regional impacts and ownership impacts are investigated.

Another contribution is that, to the best of our knowledge, this is the first work to empirically explore cost sharing strategies in technological collaborations. Different from White and Steven (2005) who investigated the gross value of collaboration cost or Bolton et al (2005) who detect cost sharing strategies in non-technological collaborations, we emphasised cost sharing between partners when technological collaboration occurs. Various hypotheses are proposed after observing the results of the econometric models, suggesting that collaboration cost may increase with R&D, the ratio of employees with a higher education background, the technology gap, and the previous collaboration cost percentage, but may decrease with transaction costs, the number of patents held by firms, the technology level and the firms' perceived price. These major findings on collaboration cost therefore differ greatly from previous researches and may be considered as new.

The third practice contribution is that we confirmed some predictions gathered from the existing empirical literatures. As suggested by Klecun-Dabrowska (2002), a good contribution may not only focus on providing alternative knowledge, but may also 'reflect or match the world as it exists'. Therefore, evidence confirming the hypotheses from existing literatures may also be considered as a contribution. In Chapter 5, a positive relationship between six hypotheses relating to three factors and innovation (collaboration) are proposed. By using various econometric techniques, we found four of them confirmed from our results. To be more detailed, we confirmed the hypotheses proposed by Castellacci (2008) that both innovative ability and absorptive capacity may positively affect firms' innovative or collaborative decisions. On the other hand, since we observed a positive and significant relationship between catching up capacity and collaboration, we partly confirmed the hypotheses proposed by Blalock and Gertler (2009) that innovation and collaboration within firms may vary with their catching up capacity.

Methodology contribution

The methodology contribution mainly comes from the MATLAB programming in Chapter 3. We employed MATLAB programmes for two purposes. One is to show how collaboration opportunity varies with market characteristics, whilst the other is to show how collaboration cost varies with market characteristics. We had two particular reasons to use the MATLAB programmes. One is that it allows us to observe the general relationship between market characteristics and collaboration cost. Since the collaboration cost may depend upon three different sub-equations, this would make our analysis excessively complicated if we discussed the three sub-equations separately. Moreover, as the first and second order of differentiation for some parameters are not constantly positive or negative, it is almost impossible to conclude on each parameter's potential impact. Using MATLAB simulation allows the programme to pick up the logical solution of each sub-equation when we input the specific value of parameters.

The other reason is that rather than revealing 2-D partial relationships between one particular characteristic and collaboration opportunity (or collaboration cost), MATLAB programmes could show the 3-D simultaneous impacts of various characteristics in a dynamic environment. In particular, by using animation programmes, it clearly shows how collaboration cost varies with the size of imitation. Since the size of imitation grows from the theoretical minimum to the theoretical maximum, it is not likely to miss any abnormal status when imitation reaches a certain value. Therefore the methodology will greatly enhance the consistency of simulation results. Different from other readily available game theory packages, in MATLAB both programmes are here introduced to the literature for the first time.

6.4 Limitations

To explore under what circumstance firms collaborate and what determinants affect collaboration cost, we firstly employed game theory to explore these two questions for different market types. We also used various econometric models to explore these two questions in the Chinese manufacturing context. However, as with all modelling there are limitations.

As mentioned in Chapter 3, for the game theory model, the limitations are mainly covered by three points which are abbreviated as follows:

1. The strategy sets we assume only contain innovation, collaboration, imitation and do nothing. There are certainly other options which might be chosen in reality, such as licensing, or outsourcing.

2. Our assumption in the game theory model does not allow for risk and uncertainty. However, firms can only try to launch new technology but cannot guarantee success. This point might be reviewed and improved in future research by using game theory with uncertainty

3. The game we illustrated is a two-player, two-stage, product innovation game between firms. More players and more stages or players with other ownership may be added in the future.

The main limitation of our empirical studies is the small size of the data sample. With three time periods, we may not explore stationarity using unit root tests (Bond et al, 2005; Blander, 2012). More variables might be found to be significant using different empirical techniques, such as the ARIMA model or the GARCH model, which may be employed with a larger sample and longer time periods.

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