Complementarity in innovation and development : a cross-country comparison

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A Cross-country Comparison

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Complementarity in Innovation and Development

A Cross-country Comparison

DISSERTATION

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by

Jun Hou

Supervisor:

Prof. Dr. Pierre Mohnen

Assessment Committee:

Prof. Dr. Robin Cowan (chair)

Prof. Dr. René Belderbos, KU Leuven

Prof. Dr. Elena Huergo Orejas, Universidad Complutense de Madrid

Dr. Boris Lokshin

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Jun Hou

Maastricht, July 2013

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Chapter 1

Introduction

1.1 Motivation: innovation in developing countries

Under the intensive pace of the globalization and technological change, innovation has been widely recognized as the main source for developing countries to gain competitiveness and catch-up. Both challenges and opportunities emerge during this catch-up process. These challenges are accentuated by the fact that the catch-up process requires more knowledge and entrepreneurial spirit to compete in an environment of intensified global competition. The opportunities arise from the possibilities for modernization of traditional activities offered by new technologies.

While there is considerable experience accumulated in the field of innovation policy in developed economies, much of this is not directly applicable to developing countries due to the nature of the characteristics these countries have. The situation is rendered more complicated because the “developing world” presents very diverse situations in terms of levels of development, culture, institution etc. Consequently, innovation policy schemes have to be tailored to countries’ specification in line with the recognized fact that “one size does not fit all”, and the recognized need for working much more on national peculiarities of development economics and policies.

The present thesis will try to investigate the potential synergistic effects which exist or might emerge among different aspects of the innovation process in developing countries.

Technological sourcing: something more than R&D

In the context of developing countries, new dimensions of the innovation concept are uncovered. Innovation should be understood as something new to a local context more than to a global context. On the one hand, it is still defined as the design and production of technologies of a worldwide significance - technology creation. On the other hand, innovation is also defined as local improvements based on the adoption of technologies, which are available from the domestic market or global market - technology adoption.

Innovation, which is mainly driven by research and development (R&D) activities, has been considerably discussed in the endogenous growth theory (Aghion and Howitt, 1998; Grossman and Helpman, 1991) and a number of empirical studies (Griliches, 1984; Hall, Mairesse and Mohnen, 2010). Besides creating new knowledge, R&D also presents another critical role for developing countries in building technological capacity (Cohen and Levinthal, 1989). However, with limited budget to allocate in R&D and a lack of innovation experience, technology creation in developing countries in general is difficult to accomplish.

Technology adoption, by which is understood learning and imitation, has been recognized as another major channel for firms in developing countries to achieve technological advances. During the catch-up phase, external technological acquisition, domestic and international, together with in-house R&D activities have a substantial influence on the speed of learning. Both internal and external sourcing are the major inputs in the innovation process. Freeman (1989) suggested that external knowledge sourcing has a significant influence on the learning process. He argued that for the most part even the most technologically advanced firms in developing countries are committed to be involved in external sourcing activities. External sourcing plays two important roles in this process: filling gaps in domestic technological capability and upgrading the existing technologies to international standards (Aggarwal, 2000). By enhancing technological capability, it consequently reinforces the return of doing in-house R&D. At the same time, in-house R&D activities also present their dual function here: developing new innovation and building technological capacity. Cohen and Levinthal (1989) define “absorptive capacity” to describe the substantial role of a stock of prior knowledge in order to absorb external know-how. They argued that the in-house R&D process would at the same time accommodate firms to build up their own technological capability.

But which technological sourcing contributes most to firms' performance in developing countries? Are there any synergistic effects between these sourcing strategies? Answers to these questions are still inconclusive. The current research will conduct an insightful analysis of technological sourcing strategies in the context of developing countries.

Individual policy or policy package?

The success of innovation also associates with several other factors, such as the technological capability in the system and obstacles faced by firms. To gain a richer picture of innovation in development, we are not only concerned with the technological sourcing strategy, but also with the obstacles to innovation and learning. Obstacles in innovation are perceived as factors which have the potential to prevent innovation decision or increase the difficulties, timeframe and cost of the process. In fact, firms in less developed countries are more likely to face genuine barriers to innovation due to inadequate experience and this is precisely why they remain a low level of development.

The potential interactions between the obstacles require different forms of policy responses. Understanding the intrinsic relation between obstacles, complementary or substitutive, is essential to formulate efficient policies. A complementary relationship between obstacles to innovation suggests that if one obstacle is present and hampers innovation, the hampering effect of the second obstacles would be eased. It indicates a positive interaction between obstacles in enhancing innovation. This interpretation is in accordance with the standard notation of complementarity given by Milgrom and Roberts (1990a) – the presence of one activity increases the marginal return of the other activity. Based on this understanding, if obstacles are complementary, the corresponding policies that aim at removing obstacles are also complementary factors. Indeed, , a complementary relationship between two obstacles suggests that policies aimed at solving both obstacles are optimal. To remove only one obstacle would amplify the hampering effects of the other. A substitutive relationship between obstacles, on the other hand, would indicate that obstacles need not be removed jointly, all policies should attempt is to avoid that obstacles appear simultaneously. With inadequate resources to solve all barriers together, this perspective would be especially valuable for developing countries.

An alternative (opposite) definition of complementary between innovation obstacles would be that of a negative interaction between them: if one obstacle is present and

hampers innovation, the second obstacle's hampering effect is strengthened. This interpretation is in accordance with the terminology "negative complementarity" that we proposed earlier chapter 2.2). Thus, having a good understanding of the nature of innovation obstacles, their pattern and impacts on the innovation outcome and firm performance is crucial for the firm and the government to conceive efficient innovation strategies and policy responses, and consequently enhance economic competitiveness (Hadjimanolis, 2003; Ferriani et al., 2008).

1.2 Investment Climate Survey for innovation studies

The empirical analysis of this thesis uses firm-level data from the Investment Climate Survey (ICS) collected by the World Bank in 135 countries from different regions of the world between 2002 and 2011. The surveys are divided in several waves by the year at which they are conducted. According to the standardized questionnaire provided, two broad waves are defined: 2002-2005 and 2006-2011¹. For each wave, there is a standardized questionnaire that covers a set of questions that are addressed in every country's survey. In general, questionnaires used in the survey are the same, or at least very similar, within a region. Larger differences are detected across regions. The regional coverage of the countries is given in Table 1.1. The table shows the number of firms that are included from each region.

Table 1. 1 Regional coverage of the countries and firms in ICS

Region	2002-2005			2006-2011		
	Number of Countries	Number of firms	Percentage of firms	Number of Countries	Number of firms	Percentage of firms
Sub-Saharan Africa	12	3,258	7.73%	37	15,276	24.18%
East Asia and Pacific	4	5,880	13.94%	10	4,952	7.84%
Eastern Europe and Central Asia	28	19,558	46.38%	30	13,286	21.03%
Latin America and the Caribbean	10	5,947	14.10%	31	25,587	40.50%
Middle East and North Africa	5	3,281	7.78%	1	477	0.76%
South Asia	4	4,245	10.07%	5	3,592	5.69%
Total	63	42,169	100%	114	63,170	100%

¹ Information regarding the full content and range of data can be found on the World Bank enterprise survey website: <http://www.enterprisesurveys.org/>

The World Bank's ICS provide a unique source of information that can be used to measure finance, corruption, infrastructure, crime, competition, labor, obstacles to growth, and firms' performance across a large set of developing countries. In each country, the sample was designed to be representative of the population of firms according to their industry and location. Many recent studies have employed ICS for cross-country comparison analysis. The merits and weaknesses of these data for analysing firms' innovation behaviors in developing countries are discussed in Gonzales and Lamanna, 2007; Almeida and Fernandes, 2008; Saliola and Seker, 2011. Here, we highlight some of them.

First, for each wave, it is conducted by using a standardized questionnaire across countries located in the same region (see Table 1.1 for region categories), collecting comparable information on several innovation related aspects at the firm level. The data cover major two-digit manufacturing industries according to the International Standard Industrial Classification (ISIC), revision 3.1. Standardized survey instruments and a uniform sampling methodology are employed to minimize measurement error. The survey addresses question on whether the firm adopted a new technology during the year under review, in-house R&D or R&D co-operative works, technology-sourcing activities such as licensing, technology importing, and other important channels to acquire technology. The survey also contains questions which capture firm characteristics such as the firm's ownership structure, age, size, human capital composition, and whether it had import and export activities. Detailed information on infrastructure, institutional background and firms' operation environment also included.

Second, compared with the Community Innovation Survey (CIS) recently conducted in European countries by the OECD (Evangelista et al., 1997; Criscuolo et al., 2005; Damijan et al., 2005; Mohnen et al., 2005), the ICS has the advantage of collecting innovation characteristics for all firms in the sample. The CIS does not include this information for firms that do not innovate during the year under review, except for UK. This advantage potentially avoids the sample selection bias which might exist in CIS. ICS is also featured by its questions that are designed in the context of developing countries. It does so by considering the fact that innovation in developing or least developed countries is a catch-up process through learning, adoption and imitation. Great attentions are placed on learning activities for which firms have used to acquire technology, particularly in the wave of year 2002. The survey collects detailed

information on the main channels used by firms to acquire technological source. These channels include importing new machinery, transferring from the parent company, or hiring key personnel or consultants, licensing from domestic or foreign sources, doing R&D internally, and doing R&D in cooperation with client firms, equipment and machinery suppliers, or other institutions (i.e., universities and public institutions, business or industry associations, trade fairs, or study groups). This unique information will assist us to do an insightful analysis about technological sourcing behavior of firms in developing countries.

Third, throughout all waves, one of the core questions covered by the ICS regards obstacles firms faced, such as factors related to finance, infrastructure, regulation, corruption, competition, labor, tax, and political instability etc. Respondents were asked to what extent each specific obstacle impeded their operation in the period under review. Dichotomous variables can be constructed to indicate whether a firm assesses them as major impediments (i.e. the corresponding variable takes the value 1 if the firm has rated an obstacle as major or very severe, and takes the value 0 otherwise). By tapping into the potential barriers of which exist in operation and innovation process, economist would gain a deeper understanding about firms' decision and activities. In addition, by investigating obstacles and their intrinsic relationship, we will be able to get a clear picture of how obstacles interact with each other and how they influence the innovation outcome. Findings will provide useful implications for government or enterprises to formulate efficient policies.

Last but not least, research on the comparison of innovation performance across developing countries has been limited due to the unavailability of a homogenous data source. The ICS collects information on innovation performance through surveys conducted across a large number of developing countries, which provides a unique opportunity to compare average innovation and productivity performance of firms across countries. In line with other survey, innovation is measured by several ways in ICS. Innovation can be indexed by a dummy - equal to one if a firm reports having introduced new technology or a significant improvement of the current technology during the period under review. Innovation can also be measured by other information such as the percentage of new products and services sales in total turnover. This share-in-sales indicator is the direct link between the innovation effort and the commercial success and has been widely used as output indicator in recent years (Mairesse and

Mohnen, 2001; Klomp and Van Leeuwen, 1999). This definition captures the creation of new knowledge but also the adoption and adaptation of production processes. It should be noted that ICS only includes share-in-sales indicator in some countries and regions, such as China 2000-2002 and Eastern Europe and Central Asia 2006-2011.

There are several shortcomings in the ICS data though. First, due to methodological changes and evolution of the survey instrument across regions and years, it is not possible to match all variables in the dataset for every country. Second, firms are also largely unbalanced across each wave. There are many firms which drop out in the following survey and also lots of new firms that enter the dataset, which rules out the possibility of having panel analyses. Another major shortcoming is that even though there are always improvements of the quality and accuracy of the data, large amount of inconsistencies can be detected especially from 2002 to 2005, such as currency inconsistencies, missing values or unreasonable answers. Therefore, it is suggested to have a thorough familiarity with the questionnaires and a detailed check of the un-standardized data for each country before proceeding with the analysis.

1.3 Outline of thesis

The present chapter introduces the topic of inquiry in this thesis and describes the data used in the empirical analysis. It follows by giving a concise outline of the remaining chapters.

The second chapter is a step towards understanding the concept of complementarity and reviews previous innovation studies in the literature that adopts the complementarity approach. It presents an insightful interpretation of complementarity between pairwise economic activities by using a hierarchical classification. Complementarity is broadly classified into two types based on whether or not it is embedded in a specific objective function: objective complementarity and behavioral complementarity. Further classifications in the lower level of hierarchy are also defined. Apart from elaborating different types of complementarity, chapter 2 also introduces the approaches adopted in empirical studies to test complementarity/substitutability. Three approaches are distinguished: CORR (Correlation approach), MP (Miravete and Pernías approach) and PROD (Production approach). Moreover, reviewing the previous studies that try to

investigate complementarity in the innovation process, it shows the problems and limitations that exist in literature. The chapter on literature review provides a detailed discussion on these problems and limitations. It also explains how they will be addressed in this thesis.

Chapter 3 investigates the existence of complementarity between in-house R&D and external technology acquisition by using a panel data of Chinese manufacturing firms. It tries to explore the impact of internal and external technology sourcing on firms' innovation and productivity performance in Chinese small- and medium-sized manufacturing firms. In particular, it estimates the returns of R&D and external technology purchasing (TP) and their possible complementarity or substitutability. It does so by distinguishing two performance measures: innovation in products or processes and labor productivity. Since size may matter in this regard, we estimate separately the relationships for firms with fewer than 100, between 100 and 300, and more than 300 employees. The findings show that in-house R&D seems to accelerate the assimilation of external know-how whereas external technology sourcing enhances the efficiency of in-house innovation activities. The results also exhibit some evidence of complementarity between in-house R&D and TP in raising the sales of new products per employee in small-sized Chinese manufacturing firms with 100 to 300 employees while R&D and TP are substitutes when it comes to raising labor productivity.

The fourth chapter is another empirical study to test potential synergistic effects between technological strategies by using firm cross-sectional data from 24 developing and least developed countries. In this chapter, we try to identify factors that determine the choice of a specific technological sourcing, as well as factors that foster the potential complementarity between them. It examines the roles of internal R&D efforts and external technology sourcing in fostering productivity in manufacturing firms. Three testing approaches are compared and adopted in the empirical analysis, namely CORR, PROD and MP (Miravete and Pernías approach, see chapter 4). The analysis emphasizes that in a cross-sectional analysis, the MP approach stands out compared with the other two approaches by providing a structural framework, which effectively corrects the bias caused by the correlation between unobservables. The empirical finding highlights the critical role of external technology acquisition in manufacturing industries across developing countries and exhibits signs of complementarity only in middle-income countries. The results also show that different approaches give different results.

Chapter 5 discusses different types of multivariate one-sided hypothesis defined to test pairwise complementarity among three or four activities. This chapter uses simulated datasets to compare the validity and efficiency of two types of hypotheses with different model specifications and sample sizes. The simulation results verify the potential bias which might exist in the non-exhaustive hypothesis formulation. Conclusions based on such hypotheses tend to be biased if the nature of the inequalities is not taken into account. Findings from this chapter also suggest that combining two tests of hypothesis always guarantees a more accurate conclusion in testing complementarity. In some situations, especially when the sample size is large and the R-square value is high for linear models, only one hypothesis testing can also provide adequate information to draw correct conclusions.

In order to gain a deeper understanding of the barriers to innovation, chapter 6 applies the complementarity approach to firm level data from the Investment Climate Survey 2009 Eastern European and Central Asian countries (EECA) to investigate if there exists complementarity or substitution among four types of obstacles to innovation across different sectors, income levels and size groups. The approach of testing pairwise complementarity when more than two activities occur, is borrowed from chapter 5. Findings from this chapter provide a clear explanation of complementarity between obstacles to innovation: the presence of one obstacle eases the hampering effect of the second obstacle to innovation. The finding suggests that a policy package that attempts to tackle both obstacles is preferred. Policies that only eliminate one obstacle would amplify the deterring effects from the other. A substitutive relationship between obstacles, on the other hand, suggests removing one obstacle is enough because its presence would worsen the negative effects induced by the other.

The final chapter concludes the dissertation, providing a number of policy implications and it recommends avenues for future studies.

Chapter 2

Complementarity in innovation studies

2.1 Introduction

Since Samuelson pointed it out in 1974, the notion of complementarity has been explained and adopted in different theories in economic research, such as comparative statics of optimal solutions (Topkis 1978; Topkis 1998); games with strategic complementarities (coincidence of normal-form solution concepts; oligopoly applications); comparative statics under uncertainty (behavior under risk; Bayesian games); and institutional complementarity (fit and synergies in organization theory; modern manufacturing; varieties of capitalism).

The notion of complementarity is commonly referred in standard price theory, where, for example, two goods are complements if raising the price of one lowers the consumption of the other. During the past two decades, this concept has been broadened to permit analyses of complex economic phenomena, organizational structures and government policies. A group of activities are defined as complements if doing more of any subset of them increases the return to doing more of any subset of the remaining activities (Milgrom and Roberts, 1990a; Matsuyama, 1995). However, complementarity may also cause deterring effects. For example, complementary factors in a system may have difficulties to adopt new organizational changes since change in one factor of the system would require change in other complementary factors in the system (Milgrom and Roberts, 1995).

The perspective of complementarity is intriguing, yet it lacks the specificity about its definition, classification and testing approach framework. In this chapter, we aim to review the general definition of complementarity and its classifications, and thereby lay the basis for the empirical analysis in the following chapters.

2.2 Definition and classification of complementarity

2.2.1 Complementarity definition

Complementarity was first introduced into economics by Edgeworth (1881) and refers to the notion: gain from increasing all factors is more than sum of gains from increasing them separately. Topkis (1978) explained the theory of complementarity by using the subject of a branch of mathematics known as lattice theory. The intuition behind sublattices is that constraining a choice to lie in a sublattice expresses a kind of technical complementarity: it suggests that increasing the value of some variables never prevents one from increasing the others as well, it may actually require increasing some, and similarly that decreasing some variables never prevents one from decreasing others. In this sense, a sublattice could be very useful to model the idea that a set of activities is complementary.

Based on the concepts of Edgeworth complementarity and sublattice supermodularity, complementarity was formally modelled in economics by Milgrom and Roberts (1990b, 1994) and their approach provides an impetus for later empirical research. They argue that complementarity in economic terminology corresponds to positive mixed-partial derivatives of a specified payoff function in a differentiable framework. The marginal returns to one variable are increasing in the levels of the other variables, and therefore the economic performance by combining two or more complementary factors in a production system is expected to be better than what would be generated by applying these factors in isolation (Ennen and Richter, 2010). The notion of supermodularity enables economists to model, in a mathematically rigorous manner, the relationships among multiple economic activities or organizational elements of complex systems as something more than the sum of these elements. Beneficial effects of such relationships are often coined fit, which has a rich intellectual tradition in economic and organizational theory (Drazin and Van de Ven, 1985).

Formally, a pair of economic activities is complementary if (1) adopting one does not preclude adopting the other and (2) whenever it is possible to implement each activity separately, the sum of the benefits to do just one or the other is no greater than the benefit of doing both together. Suppose there are two economic activities X_i and X_j , and Z is a vector of exogenous variables. In a differentiable framework, the objective function $f(X_i, X_j, Z)$ is supermodular if the incremental effect of one economic activity increases conditional on increasing another activity (Milgrom and Roberts, 1990a), which is equivalent to hold the following inequality for all values of the other arguments of f :

$$\frac{\partial^2 f(X_i, X_j | Z)}{\partial X_i \partial X_j} > 0 \quad (2.1a)$$

If X_i and X_j are discrete choices made by firm in adopting or implementing any economic activities, then the sum of adopting them separately is no greater than adopting them simultaneously with all other exogenous effects controlled:

$$f(X_i = 1, X_j = 1 | Z) + f(X_i = 0, X_j = 0 | Z) > f(X_i = 0, X_j = 1 | Z) + f(X_i = 1, X_j = 0 | Z) \quad (2.1b)$$

In the case of substitutability, the inequality signs are reversed.

2.2.2 Complementarity classification: objective complementarity vs behavioral complementarity

In order to provide a more insightful interpretation of the inter-dependent relations between pairwise economics activities, we broadly classify the complementarity into two sub-categories: (a) objective complementarity and (b) behavioral complementarity. The former is the complementarity under the framework of achieving a specific economic goal, which is in accordance with the conceptual framework proposed by Milgrom and Roberts (1990b, 1994). It is a synergy between activities that foster a better performance with respect to a specific purpose. Examples are: complementarity between innovation sourcing strategies in productivity growth; complementarity between R&D cooperation strategies in innovation output. The ‘objective complementarity’ plays a dominant role in the empirical studies of complementarity literature. One representative example is the study carried out by Mohnen and Röller (2005). The authors use the Community Innovation Survey (CIS) data from 4 European countries to test the complementarity between different kinds of innovation obstacles. Four obstacles faced by firms are

interacted and embedded in the innovation function. By systematically estimating the complementary versus substitutive relationship between pairs of obstacles, their results show that lack of internal human capital is complementary to all the other obstacles regarding the probability of becoming an innovator. Another example is the 'Make and Buy' complementarity investigated by Cassiman and Veugelers, (2006) using Belgium manufacturing firms. The authors examined the relationship between firms' internal R&D and external technology acquisition in the production function. Their finding confirms the existence of complementarity between in-house R&D and external sourcing strategy when it comes to productivity performance.

The other type of complementarity is the complementarity between economic activities in a general sense of a firm's recognition of utility or profit maximization. In this framework, no specific objective function is specified. It is based on the interpretation that a firm's choice of adopting activities simultaneously will in one way or another accomplish the optimal utility goal. Normally, empirical studies adopting this notation come with the assumption that firms are believed to undertake rational choices based on their individual understanding of maximizing utility. Due to the nature that it is a general behavior of adoption and decision-making, we define this type of mutual effects as 'behavioral complementarity'. A representative study in line with this notion was conducted by Arora and Gambardella (1990). They tested the synergetic effects among four different external sourcing strategies of large chemical and pharmaceutical firms by looking at the conditional correlation coefficients. After controlling for firms' specificities, the results show significant correlation coefficients between all types of external sourcing strategies. The authors conclude that if any two strategies are complementary then they are positively correlated. Several studies that try to investigate the innovation cooperation strategies also adopt the correlation coefficients (bivariate or multivariate analysis) as indicators for complementarity (Belderbos et al., 2004; Tether, 2008; Schmiedeberg, 2008).

Figure 2.1 Complementarity classifications

Symmetric complementarity vs asymmetric complementarity

As shown in figure 2.1, subcategories are further defined under the framework of objective complementarity. The symmetric complementarity and asymmetric complementarity were introduced by Choi and Poon (2008). If two or more economic activities affect the objective function in the same direction, then they are defined as ‘symmetric complementary’ activities. A further sub-classification can be made in the symmetric complementarity: ‘positive symmetric complementarity’ and ‘negative symmetric complementarity’. The synergistic effect that arises from variables with positive estimated coefficients is referred to ‘positive symmetric complementarity’. On the contrary, the synergistic effects that exist among variables with negative sign are referred to ‘negative symmetric complementarity’ (For more details, see Chapter 6.3.1). For example, for the innovation output function (patent or new products sales), strategies such as R&D cooperation and technological sourcing are expected to stimulate innovation outcome while factors such as obstacles (finance, tax, regulation etc.) might inhibit innovation outcome. If X_i and X_j are in a differentiable form then:

$$\begin{aligned}
 &\text{with the presence complementarity } \frac{\partial^2 f(X_i, X_j | Z)}{\partial X_i \partial X_j} > 0 \\
 &\left\{ \begin{array}{l} \text{Positive complementary: if } \frac{\partial f(X_i, X_j | Z)}{\partial X_i} > 0 \text{ and } \frac{\partial f(X_i, X_j | Z)}{\partial X_j} > 0 \\ \text{Negative complementary: if } \frac{\partial f(X_i, X_j | Z)}{\partial X_i} < 0 \text{ and } \frac{\partial f(X_i, X_j | Z)}{\partial X_j} < 0 \end{array} \right. \quad (2.2a)
 \end{aligned}$$

In the case of X_i and X_j are both binary choice activities

$$\begin{aligned}
& f(X_i = 1, X_j = 1 | Z) + f(X_i = 0, X_j = 0 | Z) > f(X_i = 0, X_j = 1 | Z) + f(X_i = 1, X_j = 0 | Z) \\
& \left\{ \begin{array}{l} \text{Positive complementary: if } \frac{f(X_i = 1, X_j = 0 | Z)}{f(X_i = 0, X_j = 0 | Z)} > 1 \text{ and } \frac{f(X_i = 0, X_j = 1 | Z)}{f(X_i = 0, X_j = 0 | Z)} > 1 \\ \text{Negative complementary: if } \frac{f(X_i = 1, X_j = 0 | Z)}{f(X_i = 0, X_j = 0 | Z)} < 1 \text{ and } \frac{f(X_i = 0, X_j = 1 | Z)}{f(X_i = 0, X_j = 0 | Z)} < 1 \end{array} \right. \quad (2.2b)
\end{aligned}$$

‘Asymmetric complementarity’ describes the situation that not all activities present positive effects in affecting the outcome under the objective function: at least one of the activities shows a negative sign or no effect on the outcome. In the case of only two activities X_i and X_j , asymmetric complementarity is identified if only $X_i(X_j)$ positively influences outcome independently of the other, and the presence of $X_j(X_i)$ creates a catalysis effect that further enhances the positive impact of $X_i(X_j)$ instead of directly influencing the outcome.

If X_i and X_j are in a differentiable form then:

$$\begin{aligned}
& \text{with } \frac{\partial f(X_i, X_j | Z)}{\partial X_i \partial X_j} > 0 \\
& \text{Asymmetric complementary: if } \frac{\partial f(X_i, X_j | Z)}{\partial X_i} > 0 \text{ or } \frac{\partial f(X_i, X_j | Z)}{\partial X_j} > 0 \quad (2.3a)
\end{aligned}$$

In the case of X_i and X_j are binary choice activities,

$$\begin{aligned}
& f(X_i = 1, X_j = 1 | Z) + f(X_i = 0, X_j = 0 | Z) > f(X_i = 0, X_j = 1 | Z) + f(X_i = 1, X_j = 0 | Z) \\
& \text{Asymmetric complementary: if } \frac{f(X_i = 1, X_j = 0 | Z)}{f(X_i = 0, X_j = 0 | Z)} > 1 \text{ or } \frac{f(X_i = 0, X_j = 1 | Z)}{f(X_i = 0, X_j = 0 | Z)} > 1 \quad (2.3b)
\end{aligned}$$

Based on the classification introduced above, the next section will describe the approaches used to test complementarity.

2.3 Approaches for testing complementarity

2.3.1 CORR approach

If the presence of one practice is likely to raise the marginal effect of other practices, then the joint adoption of two practices together should be encouraged. Therefore, if there is a co-movement phenomenon of two practices, it can be interpreted as the first

evidence in favour of existing complementarity. This co-movement may be indexed by the positive correlation (negative if substitutes) between pairwise practices and the approach used to identify the correlation coefficient is defined as ‘Correlation approach’ (CORR)². This approach is easy to implement and mainly focuses on testing ‘behavioral complementarity’ in the sense that synergies between activities are captured without looking at the relative performance outcomes. Empirical studies that take this approach may use, as independent variables, either dichotomous variables (if an activity is implemented), rank-ordered or continuous measures of the factor concerned. The main statistical methods applied consist of the Pearson correlation coefficient, bivariate and multivariate conditional regressions. Some studies on complementarity use this approach as auxiliary evidence (Cassiman and Veugelers, 2006; Schmiedeberg, 2008).

Several drawbacks of the CORR approach should be noted here. First, using Pearson correlation can only provide very preliminary results with regard to the fact that heterogeneity always produces noise in the practice adoption process. Without holding the firm characteristics fixed, it is very unlikely that the pairwise correlation coefficient can generate consistent results. Second, in order to control for firm characteristics, bivariate probit or multinomial model have been used to test the complementarity by looking at the correlation between residuals. This method may successfully investigate factors which cause the correlation. For example, if the correlation coefficient decreases when factors are added, then one would argue that these factors are the causes of complementarity. However, the CORR approach is limited by the strong assumption imposed: firms are believed to make the optimal decision in adopting activities or choosing strategies concerned. Moreover, we do not know whether the correlation between residuals is the results of an actual complementarity or the association between unobserved errors (Athey and Stern, 1998; Miravete and Pernías, 2006).

2.3.2 Production approach (PROD or system approach)

In contrast, the approach that takes into account the performance outcomes with a specific objective function is defined as ‘Production approach’ (PROD)³. It has been widely applied to investigate complementarity in the economic and management literatures. The PROD approach looks directly at the cross partial returns in the objective

² The CORR approach is also defined as ‘Adoption approach’ (Miravete and Pernías, 2006).

³ The PROD approach is also defined as ‘System approach’ (Enne and Richter, 2010).

function and has been applied in several empirical studies (Cassiman and Veugelers, 2006; Mohnen and Röller, 2005; Belderbos et al., 2006).

First, in order to implement the PROD approach, an objective function needs to be established. Suppose there are two economic activities X_i and X_j and Z is a vector of exogenous variables in an objective function $f(X_i, X_j, Z)$. The PROD approach regresses an objective on exclusive combinations of innovation activities.

$$f(X_i, X_j, Z) = \theta_{00}(1 - X_i)(1 - X_j) + \theta_{10}X_i(1 - X_j) + \theta_{01}(1 - X_i)X_j + \theta_{11}X_iX_j + \theta_z Z + e \quad (2.4)$$

where X_i and X_j are dichotomous choices that take value 1 if they are adopted by the firm. θ_{11} stands for the cross-partial returns of choosing both X_i and X_j jointly; θ_{10} for choosing X_i only; θ_{01} for choosing X_j only; θ_{00} for choosing none of them. The objective function is supermodular in X_i and X_j if

$$\theta_{11} - \theta_{01} - \theta_{10} + \theta_{00} > 0 \quad (2.5a)$$

It demonstrates that the return to adopting both activities is greater than the sum of performing them in isolation. On the other hand, it is submodular and hence the choices are interpreted as substitutes if

$$\theta_{11} - \theta_{01} - \theta_{10} + \theta_{00} < 0 \quad (2.5b)$$

Another alternative form to express the supermodularity in the objective function can be expressed as $\theta_{ij} > 0$. The objective function now defined as

$$f(X_i, X_j, Z) = \theta_0 + \theta_i X_i + \theta_j X_j + \theta_{ij} X_i X_j + \theta_z Z + e \quad (2.6)$$

where

$$\begin{aligned} \theta_0 &= \theta_{00} \\ \theta_i &= \theta_{10} - \theta_{00} \\ \theta_j &= \theta_{01} - \theta_{00} \\ \theta_{ij} &= \theta_{11} + \theta_{00} - \theta_{10} - \theta_{01} \end{aligned} \quad (2.7)$$

where the coefficient θ_i captures the non-exclusive partial effect of X_i ; θ_j the non-exclusive partial effect of X_j ; θ_{ij} the return from adopting make and buy together; θ_0 is

constant. If we insert (2.7) into (2.6), we will get back to equation (2.4). Hence, the condition for the production function (2.5) to be supermodular can be simplified as one-side t-test on $\theta_{ij} > 0$. It is clearly shown in function (2.6) that the marginal returns of either X_i and X_j will not be constant anymore if complementary or substitutive effects are observed (shown as $\theta_{ij} \neq 0$). The complementarity coefficient appears in the estimation of partial effects of each of the strategy. The marginal returns of X_i and X_j to the performance outcome can be expressed respectively as

$$\begin{aligned} [f | X_i = 1] - [f | X_i = 0] &= \theta_i + \theta_{ij}X_j \\ [f | X_j = 1] - [f | X_j = 0] &= \theta_j + \theta_{ij}X_i \end{aligned}$$

Athey and Stern (1998) explained that simply running OLS on the above function would deliver inconsistent results. They argued that the existence of firms' unobserved heterogeneity may have a substantial influence on the association between strategies even though complementarity may not exist at all. Consequently, the PROD approach might deliver biased results if there are unobserved factors in the error term that are correlated with the activities the firm adopted – the endogeneity problem.

In order to correct for this bias, a structural model should be developed, either using instruments in the cross sectional data or panel method if the panel data are available (Wooldridge, 2002). Cassiman and Veugelers (2006) have tried to adopt instrumental variables that were correlated with the adoption decision without affecting innovation output. However, the results can be refined only if the instrumental variables are properly identified. Therefore, the PROD approach possibly suffers from biases because of the endogeneity of input strategies.

2.4 Complementarity in innovation: patterns in the literature

Our review of the literature consists of forty-two empirical studies⁴ that reveal the substance of 'synergy' or 'fit' in innovation regarding both economic and management issues. The selected studies concern complementarity assets in different aspects of

⁴ This literature survey tries to include studies that address complementarity assets in innovation. However, the list is certainly not exhaustive.

innovation and the selection is not exhaustive. Of the studies that investigate synergistic effects in innovation, the clear majority focuses on developed economies, thirty-seven out of forty-three studies (88.1 per cent). Limited evidence exists in the context of developing or least developed countries. Except for three studies that used industry as their unit of analysis (Aggarwal, 2000; Rothaermel, 2005; Bin, 2008), most analyzes were based on firm level (organization level) data. We also noticed that almost 67 percentage of studies reviewed here adopt cross-sectional data on complementarities, using static measures of performance (e.g., productivity, patent or innovation sales) as their dependent variables. There are relatively fewer studies (about 33%) taking a longitudinal perspective. To check the full list of studies reviewed in this chapter, please see Appendix 2A.

Figure 2.2 Percentage of studies reviewed across income-level, data unit and data nature

Types of activities concerned

Figure 2.2 classifies the studies according to the types of variables for which complementary was examined. In total, eight types of activities are allocated in different stages of the innovation process. The types of complementary factors are not restricted to only one stage of the innovation. For example, the innovation obstacles can also appear in the other two stages and firms' technological capabilities tend to influence the entire innovation process. Another issue regarding the groups of factors is that some studies address topics overlapping two groups. For example, complementarity between

FDI and R&D cooperation is associated with both the technological cooperation and technological sourcing group. But in our statistics, each of the studies reviewed will be included in only one group.

Figure 2.3 Number of studies on complementarity in innovation: patterns across activities concerned

Fourteen (32.5 percentage) of the forty-three studies analyzed the interplay between technological acquisition strategies such as internal and external, foreign direct investment and technology importing etc. The findings of these studies are mixed in terms of the synergistic effect among different types of technological sourcing strategies. An interesting pattern is that studies carried out in developed economies (Cassiman and Veugelers, 2006; Lokshin et al., 2008) are likely to confirm the complementary effects while some studies using samples from developing countries found evidence of substitutive effects (Basant and Fikkert, 1996). This pattern raises a question. Does the complementarity relationship between technological sourcing depend on the level of development?

Another set of relationship that has drawn a lot of attention at the technology acquisition stage are the R&D cooperation activities. There are eight (18.6 per cent) studies in our sample that tried to search for complementarity between these co-operative activities. Of these studies, the majority found that the technological cooperation activities could create complementary values to the firm, associating with firm characteristics and specific types of cooperation. For example, Belderbos et al. (2006) analyzed the relationship among four types of R&D co-operative activities (with competitors, clients, suppliers, and universities and research institutes) in Dutch firms. Their results suggest that small

firms are likely to pursue co-operative strategies and cooperation with customers helps to increase market acceptance.

At the stage of assimilating knowledge, three groups of factors have received significant attention in the empirical literature regarding complementarity, firms' technological capability, technological infrastructure (e.g. IT) and organizational resources. Eight (18.6 per cent) of the forty-three studies have investigated synergistic effects among firms' technological capabilities such as product technology capability and product marketing capability (Moorman, 1999; Nerkar and Roberts, 2004); international R&D and research capabilities (Penner, Hahn and Shaver, 2005) and absorptive capacity and networking capabilities (Tether and Tajar, 2008). Three studies included in our review searched for complementarity between innovation infrastructure factors. Powell (1997) studied the interdependent relationship between information technologies (ITs) and its complementary assets. The findings suggest that firms with complementary human and business resources such as flexible culture, strategic planning-IT integration, and supplier relationships, have gained advantages by using ITs. But ITs alone have not produced sustainable performance advantages in the retail industry. Similar evidence was also found by Zhu (2004), whose finding confirms complementarity between e-commerce capability and information technology infrastructure by looking at their interaction in firm performance in the retail industry. Equally, three of forty-three studies are included in the category of organization resources (Colombo and Mosconi, 1995; Chung and Singh, 2000; and Gilsing etc., 2008).

Four studies in our literature review regarding complementarity in innovation have investigated the synergistic effect in human resources practices. All of these four studies found complementary gains from combining different kinds of human resource strategies. Ichniowski, Shaw, and Prennushi (1997) found productivity gains from adopting a set of work practices simultaneously such as incentive pay, teams, flexible job assignments, employment security, and training etc. Laursen and Foss (2003) test complementarities among seven types of human resource management practices by using 1,900 Danish business firms and their findings confirm the existence of complementarity in affecting innovation performance positively. Colombo (2005) uses 506 Italian young firms that operate in high-tech industries in both manufacturing and finds evidence that there are synergistic gains from the combination of economic-managerial and scientific-technical education, on the one hand, and technical and commercial industry-specific

work experience, on the other hand. Bonaccorsi (2007) shows the institutional and human capital complementarities on patenting activity by employing patent data on NANO science from the year of 1989 to 1999.

Finally, a few studies (2 out of 43) address complementarity relationships between obstacles faced by a firm during the innovation process. Such as complementarity between financial and skilled labor obstacles, and complementarity between regulatory and institutional obstacles. To have a good understanding between innovation obstacles will consequently help the firm's managers or policy-makers to lay down effective policies for helping firms to achieve successful innovation. Galia and Legros (2004) showed that due to the existence of complementarity, adopting a package of policies increases the pace of innovation for French firms. More evidence in terms of complementarity in innovation obstacle was contributed from Mohnen and Röller (2005). They used a firm-level dataset from four European countries, and systematically estimated the pairwise complementarities between four types of innovation obstacles. The findings of their study provide the evidence regarding the existence of complementarity in innovation obstacles, but it depends on the phase of innovation that is targeted i.e. the probability of becoming an innovator and the intensity of innovation. Only one paper out of forty-three was testing the synergistic effect in innovation outcomes (Miravete and Pernías, 2006). The author adopted a structural equation system to distinguish the complementarity and correlation caused by unobserved heterogeneities of firms in Spanish ceramic tile industry.

2.5 Summary: problems and limitations

Our review has shown that a gradual development has been made with respect to investigating the role of complementarities in innovation studies from an empirical point of view. As indicated earlier, the findings of the forty-three studies analyzed here are relatively encouraging, with the studies covering various subjects and supporting the existence of complementarities throughout the innovation system, also with substitutive relationships unveiled or neither complementarity nor substitution.

In conclusion, we want to raise the limitations and the problems that might be encountered for future analysis.

Gaps in the literature: the majority of studies of complementarity in innovation are focused on the developed economy context, few studies target developing countries

Overall, thirty-six studies (83.7 per cent) out of forty-three empirical studies showed evidence from developed economies. In comparison, we found substantially fewer studies (six in total, representing just 13.9 per cent of the forty-two papers) that used evidence from developing countries. In particular, all six studies were trying to investigate the potential complementarity in issues related to technological sourcing activities, topics of other aspects of innovation are relatively scarce⁵. In order to build up their competitive advantages and foster productivity growth, firms in developing countries are trying to catch-up the technology frontier through learning and imitation. Synergistic effects among innovation activities or strategies play the role of catalysts that consequently contribute to the effectiveness of catch-up process. The current study is expected to fill this gap, which will mainly focus on investigating complementarities among economic activities along the innovation process in the context of developing countries. Chapter 3 and chapter 4 will discuss complementarity between technological sourcing strategies in Chinese manufacturing firms and in other developing countries respectively. A comparison of innovation obstacles across developed and developing countries will be studied in Chapter 6.

Empirical difficulties in testing 'objective complementarity' with more than 2 activities

When testing 'objective complementarity' by using the PROD approach involving more than two activities, a system of equations that includes all the interaction terms is suggested in order to draw consistent conclusions. By only incorporating the cross-terms of two activities each time in the objective equation (Single cross-term)⁶ or including all pairs cross-terms (All cross-term)⁷ is likely to generate biased estimation due to the fact that these two tests ignore the cross partial effects between extra activities and the cross-terms (including the third-order interactions, the fourth-order etc.).

With twenty-eight out of forty-three studies reviewed that adopt the PROD approach, there are twenty studies that tried to test pairwise complementarity with more than 2 activities involved. Only two of them have adopted the equation with full cross terms

⁵ There might be studies that cover innovation complementarity issues in developing countries but these are not included in our review.

⁶ See example from Bresnahan et al., 2002; Black and Lynch, 2001.

⁷ See example from Caroli and Van Reenen, 2001.

embedded (Mohnen and Röller, 2005; Belderbos et al., 2006). Due to the complexity of test statistics in multiple-inequality constrained equation, most of the studies suffer from the potential bias that might be caused by ignoring the full extra set of interaction terms (the third-order, the fourth-order etc.). Chapter 5 will try to address this issue in detail and discuss different types of one-sided tests of hypotheses adopted in an objective function with more than two activities. It highlights that it is essential to have two tests of hypotheses to guarantee a better statistical power in the case of multiple inequality constraints. A simulation experiment will be employed for the analysis. Chapter 6 adopts the findings to investigate the interplay relationship between four types of obstacles faced by a firm in the innovation process.

Theoretical shortcomings

Overall, the complementarity perspective allows identifying complementarities only ex post on the basis of their performance effects (Athey & Stern, 1998). It does not provide the framework of ex ante with respect to the nature of activities among which synergistic effects exist or the conditions under which they emerge (Ennen et al., 2010). A number of papers adopt quantitative approaches and attempt to measure the distinct interplay relationship among activities in the innovation system. Normally, they use dichotomous variables to indicate whether particular factors concerned are in place or not. They provide little information on the strength of synergy caused by the level of activities. By employing continuous variables to measure firms' technological sourcing investment, chapter 3 of the current thesis tries to tackle this shortcoming.

The complementarity also raises some research challenges. One of them is to estimate empirically the depth and strength of the complementarity effects: how intense are various factors of the system linked with respect to the performance? Chapter 3 of this thesis tries to address this issue by estimating complementarity between continuous measures, and therefore the intensity of complementarity can be estimated. Another challenge is the potential endogeneity of complementarity. Chapter 4 explores this issue by differentiating the actual synergistic effects from the correlations between unobserved errors.

Appendix 2A Studies of complementarity in innovation

Authors	Activities concerned	Data sample	Method	Findings
Arora, 1990	External linkage of the large firms with other parties	Large chemical and pharmaceutical producers	Corr	Complementary
Colombo and Mosconi, 1995	Flexible Automation paradigm	Italian metal working industry, 783 plants	Corr	Complementary
Basant and Fikkert, 1996	R&D expenditures, technology purchases, and international and domestic R&D spillovers	Indian firms from 1974-75 to 1981-82	Prod	Substitutive
Helfat, 1997	R&D capabilities and complementary assets	US petroleum industry from 1970s to early 1980s.	Corr	Complementary
Powell, 1997	ITs and human and business resources	US retail industry	Corr	Complementary
Moorman, 1999	Product technology capability and product marketing capability	22 different product categories.	Corr	Complementary
Aggarwal, 2000	R&D efforts and technology imports	India industry level data 1982-1990	Corr	Complementary
Chung and Singh, 2000	Resource such as investors, headquarters location, geographical strength and industry strength)	US investment banking firms during 1980s	Prod	Complementary
Rothaermel, 2001	Strategic exploration and exploitation alliances	889 strategic alliances of pharmaceutical companies	Prod	Complementary
Baer and Frese, 2003	Climates and adoption of innovations	47 mid-sized German companies	Prod	Complementary
Laursen and Foss, 2003	Different human resource management practices	1,900 Danish business firms	Corr	Complementary
Miotti and Sachwald, 2003	R&D co-operation with different partners	French CIS2	Prod	Complementary
Galia and Legros, 2004	9 types of innovation obstacles	French CIS2	Corr	Mixed
Zhu, 2004	E-commerce capability and information technology (IT) infrastructure	114 companies in the retail industry	Prod	Complementary
Nerkar and Roberts, 2004	Technological and product-market experience	534 'significant' new products	Prod	Complementary
Colombo, 2005	The growth of new technology-based firms and the human capital of founders	506 Italian young firms	Prod	Complementary

Penner Hahn and Shaver, 2005	International R&D and research capabilities	65 Japanese pharmaceutical firms from 1980 to 1991	Prod	Complementary
Hu, Jefferson and Jinchang, 2005	domestic R&D, technology transfer, and foreign direct investment	China's large and medium-sized enterprises	Prod	Mixed
Mohnen and Röller, 2005	Four types of obstacles	CIS from four European countries	Prod	Mixed
Rothaermel and Hill, 2005	Generic assets and specialized assets	Panel data over a 26-year	Prod	Mixed
Song, Droge, and Hanvanich, 2005	Marketing capabilities and technological capabilities	U.S. joint ventures formed between 1990 and 1997	Prod	Complementary
Arora and Ceccagnoli, 2006	Technology licensing and the effectiveness of patent protection	1994 Carnegie Mellon survey in the US	Corr	Complementary
Miravete and Pernías, 2006	Product and process innovation	Spanish ceramic tile industry	MP	Complementary
Cassiman and Veugelers, 2006	Internal R&D and external knowledge acquisition	CIS 1,335 Belgian manufacturing firms	Prod	Complementary
Belderbos, Carree, and Lokshin, 2006	R&D cooperation with different partners	Dutch CIS in 1998	Prod	Complementary
Colombo, Grilli, and Piva, 2006	Patent holding and commercial alliances	Italian young high-tech observed from 1994 to 2003	Corr	Complementary
Bocquet and Brossard, 2007	Strategies, organization and information technologies	French firms located in Haute-Savoie	Prod	Complementary
Bonaccorsi, 2007	Institutional and human capital practices	Patent data on NANO science, 1989-1999	Prod	Complementary
Ichniowski, Shaw, and Prennushi, 2007	Among different types of work practices	36 homogeneous steel production lines owned by 17 companies	Prod	Complementary
Rothaermel and Hess, 2007	Antecedents to innovation located at the intersections across different levels	Panel data: pharmaceutical companies from 1980 to 2001	Prod	Mixed
Toole, 2007	Public basic and R&D investment	Panel of medical classes observed over 18 years	Corr	Complementary
Bin, 2008	R&D, foreign transfer, domestic transfer, and inter-industry R&D spillover	Chinese large- and medium-sized manufacturing enterprises over the period of 1996–2001	Prod	Complementary

Choi, Poon and Davis, 2006	Different types of knowledge management strategies	131 Korean firms	Corr	Mixed
Liu and Buck, 2007	Foreign R&D activities and absorptive capacity	Chinese high-tech industries enterprises	Prod	Complementary
Belderbos et al., 2008	Intra-firm technology transfer and R&D in foreign affiliates	Japanese multinational firms: 1996-1997, 1999-2000.	Prod	Complementary
Gilsing et al., 2008	Position, technological distance and network density	Alliance networks in the pharmaceutical, chemical and automotive industries	Prod	Complementary
Hashai and Almor, 2008	Integration of R&D, production and marketing activities	52 firms out of 140 Israeli industrial firms in the year 2000	Prod	Complementary
Lokshin, Belderbos, and Carree, 2008	Internal and external R&D	6-year panel of Dutch manufacturing firms (CIS)	Prod	Complementary
Roper et al., 2008	Horizontal, forwards, backwards, public and internal knowledge sourcing activities	Irish innovation panel (IIP) 1991-2002	Prod	Complementary
Tether, 2008	Specialist knowledge providers	UK's CIS3	Corr	Mixed
King and Kesner, 2008	Marketing resources and target firm technology resources		Prod	Complementary
Schmiedeberg, 2008	Internal R&D, R&D contracting, and R&D cooperation	German CIS 3	Corr	Complementary
Li, 2011	In-house R&D, importing technology, and domestic technology	Panel dataset of 21 high-tech sectors during the period 1995–2004	Prod	Mixed

Chapter 3

Complementarity between in-house R&D and technology purchasing: evidence from Chinese manufacturing firms⁸

3.1 Introduction

In order to catch up with the current technological frontier, firms in developing countries have been striving to promote technological advancement through internal research and development efforts (in-house R&D) as well as through external technology purchasing (TP). In-house R&D expenditure includes the capital, labor and design costs associated with research and development. TP involves purchasing, transferring or licensing new technologies from the domestic or the international market. For firms in developing countries, establishing efficient innovation strategies could accelerate their technological advance and contribute to their economic development.

In China, the central government has established a series of policy incentives to encourage firms to carry out in-house R&D activities⁹, and these policies have greatly increased China's capability to develop its own technology, and to assimilate and improve the technology transferred from advanced economies (Lu and Lazonick, 2001).

⁸ This is a joint paper with Prof. P. Mohnen that was published in Oxford Development Studies, Volume: 41, Issue: 03, pages 343 - 371.

⁹ Especially after 1995, policies were designed to accelerate indigenous science and technology development. The number of patent applications from domestic applicants was 10,011 in 1995, and it has increased dramatically ever since. The number reached 39,806 by 2002 and 255,832 by 2011 (China Patent Office, 2012). <http://www.english.sipo.gov.cn/>.

With great emphasis placed on ‘indigenous innovation’¹⁰, do Chinese firms still need external technology sourcing? Is there synergetic benefit from engaging in both internal R&D and technology purchasing? The goal of this research is to answer these questions by testing whether there is a relationship of complementarity between the two sources of knowledge acquisition. In other words, do R&D reinforce each other in achieving higher innovation output and/or higher levels of productivity?

The data on which the empirical analysis is based come from the World Bank Investment Climate Survey (ICS)¹¹ relating to China in the year 2003. This dataset provides continuous data on R&D and technology purchases. The results exhibit some evidence of complementarity between in-house R&D and TP in raising the sales of new products per employee in small-sized Chinese manufacturing firms with 100 to 300 employees. In-house R&D seems to accelerate the assimilation of external expertise, while external technology sourcing enhances the efficiency of in-house innovation activities. However, we find that R&D and TP are substitutes when it comes to raising labor productivity. Only for firms with fewer than 100 employees, is there a complementarity visible in terms of labor productivity.

The next section sets the background by reviewing the existing evidence on complementarity between internal and external technology acquisition in developing countries and by describing the evolution of the policy of technology acquisition in China. Section 3.3 defines the notion of complementarity and the specification of the model used in the empirical analysis. The data and the variables used will be presented in section 3.4. The results are interpreted in section 3.5. Section 3.6 summarizes and concludes.

3.2 Background

3.2.1 In-house R&D and technology purchasing: complements or substitutes?

A large number of empirical studies have estimated the relationship between innovation sourcing strategies in developing countries. Results are mixed. One group of studies concludes that internal R&D and external technology are substitutes for each other.

¹⁰ Indigenous innovation means “to develop the capability of conducting R&D or create innovation internally”.

¹¹ For more information on the Investment Climate Survey, see <http://www.worldbank.org>

Firms decide to develop technology by themselves and/or buy it from outside given a limited budget. An increase in either of the two options, therefore, tends to reduce the spending incurred on the other one. Mytelka (1987) found that external imports of technology discouraged Andean group countries from undertaking in-house innovation activities. Fikkert (1993) regressed technology imports on in-house R&D efforts and also found a negative relationship between technology imports and R&D efforts in Indian manufacturing firms. Basant and Fikkert (1996) estimated the returns on R&D, technology imports and their interaction using Indian firm level panel data. They found substitutability between R&D effort and external technology in the production of knowledge. Katrak (1997) found that the probability of importing technology is only weakly influenced by R&D efforts, and Blonigen and Taylor (2000) also conclude that firms either make or buy technology.

Another group of studies concludes that in-house R&D and external technology purchasing are complementary strategies. According to the notion of absorptive capacity proposed by Cohen and Levinthal (1989), the successful use of external technology requires the ability to assimilate external technology and apply it internally. As suggested by Fu, Pietrobelli and Soete (2010), a crucial condition for the effective transfer of technology to developing countries is their level of absorptive capacity. In this sense, parallel indigenous innovation efforts are complementary to international technology diffusion. The studies by Desai (1989), Lall (1989) and Mowery and Oxley (1995) confirm the view that technological capability is needed in order to understand the tacit components of foreign technology. Besides, acquiring technology externally helps to improve the efficiency of doing in-house R&D. As Aggarwal (2000) points out, external technology sourcing plays two important roles in developing economies: filling gaps in domestic technological capability and upgrading the existing technologies to international standards. By enhancing technological capability, it may consequently stimulate in-house R&D. Braga and Willmore (1991) found that there is a robust complementary relationship between technology buying and firm technology effort in Brazilian industry. Deolalikar and Evenson (1989) and Kim and Nelson (2000) come to the same conclusion on the basis of Indian data. A number of studies have tested a slightly different but related hypothesis based on data from developed countries, namely the existence of complementarity between internal and external R&D: Arora and Gambardella (1990) for large US, European, and Japanese biotechnology firms,

Cassiman and Veugelers (2006) and Veugelers (1997) for Belgian manufacturing firms, Bönte (2003) for West-German industry data, and Belderbos et al. (2008) for Dutch firm data. Most of the studies share the view that internal and external R&D are complementary, although Audretsch, Menkveld and Thurik (1996) find that the complementarity applies only for high-technology industries.

3.2.2 Country background

China has been the fastest growing major economy in the past 30 years with an average annual GDP growth greater than 10 per cent. Around 8 per cent of the total manufacturing output in the world comes from China, and it ranks third worldwide in industrial output¹². The extraordinary performance of the Chinese economy makes it very interesting to study its technology acquisition behavior and to examine whether such acquisition contributed to the growth performance of its manufacturing firms.

In the 1950s, China began to acquire technology externally. At first, the major source of technology was the former Soviet Union. Then, western countries and Japan became the main suppliers of technology to heavy industry. After the economic open-door policy launched in 1976, importing external technology constituted an essential component of the Four Modernisation Programmes (Zhao, 1995). Technology transfer became diversified through the purchase of turnkey plants and equipment, through foreign direct investment (FDI), and in the form of disembodied technology including licensing, technical consulting, technical service and co-production. Another feature is that the source of technology widened. Five countries - the USA, Japan, Germany, France and the UK – dominated the supply of technology to China at that time. After the economic reform of 1978, other industrial countries and regions, such as Canada, Italy, Taiwan and Hong Kong, played an increasing role in providing technology to China (Zhang, 1990; Liu, 1992; Zhao, 1995). In 1985, the central government initiated the science and technology system reform, which defined the acquisition of foreign technology as one of the main technology sourcing strategy for promoting technological development. After 1995, policies were designed to accelerate indigenous science and technology development by creating incentives and providing support for firms to establish R&D departments. As a result, these units increased dramatically, from 7000 in 1987 to over

¹² For more detailed information the reader is referred to http://en.wikipedia.org/wiki/Economy_of_the_People%27s_Republic_of_China

24,000 by 1998 (China Science and Technology Statistics, 1992, 1998)¹³, and the R&D expenditure grew annually by more than 20 per cent from 1995 to 2003 (OECD, 2006). However, when set against China's rapid economic growth, its ratio of R&D to GDP still remarkably low (1.13 per cent in 2003) compared with the OECD countries (2.25 per cent in 2003)¹⁴.

The reform of Chinese state-owned enterprises ("SOEs") was a critical part of establishing the indigenous innovation system. Unlike the private sector with no government financial support since the reforms began in the 1980s, the SOEs have remained a persistent drain on government resources (Steinfeld, 1998; White, 2000). In order to encourage SOEs to introduce new products rather than simply producing more of their existing products, the government introduced investment tax incentives (Rawski, 1994; White, 2000). Particularly since 1993, the innovation policy was sharply focused on reforming SOEs. Evidence has shown that SOEs became more strategic and dynamic in innovation in reacting to competitive pressures (Luo et al., 1998). Managers of SOEs were being granted greater responsibility and decision making power (Child, 1994; Guthrie, 1997; Walder, 1989), especially for meeting profit-based and efficiency-based measures of performance (Groves et al., 1994; White and Liu, 1998).

Like other developing countries, China has two main objectives in acquiring foreign technology: to enhance technological capability and to facilitate economic growth by increasing productivity. It is interesting to examine these issues after China's transition to a market economy, a period during which it experienced unprecedented changes in its social, legal, and economic institutions (Zhou, Yim and Tse, 2005). Table 3.1 presents some selected studies which analyse the relationship of internal and external technological sourcing in China. Although the external technology alone does not always have a significant impact on innovation, in general, the findings confirmed the complementary relationship between in-house R&D and external technology sourcing (e.g. Liu and Buck, 2007; Liu and Zou, 2008; Bin, 2008; Li, 2011; Li and Wu, 2010).

¹³ Source: Ministry of Science and Technology of the People's Republic of China: <http://www.most.gov.cn/eng/>

¹⁴ Main source: OECD library, http://www.oecd-ilibrary.org/economics/oecd-factbook-2005_factbook-2005-en

Table 3.1 Literature on the complementarity in technology sourcing in China

Study by	Data	Dependent variables	Technology sourcing	Method ¹⁵	Findings
Zhao, 1995	Heavy industries, firm level data, 1960-1991	Output; export value	R&D and technical upgrading	CORR	Imported technology complements R&D
Liu and White, 1997	Industry level data, 1987-1993	New product sales	R&D personnel and technology imports	PROD OLS	R&D complements technology transfer
Hu et al., 2005	Large and medium-sized enterprises, 1995-1999	Productivity	R&D, technology transfer and FDI	PROD IV	R&D complements technology transfer
Liu and Buck, 2007; Liu and Zou, 2008	High-tech industry, with annual turnover above 5 million RMB, 1997-2002	New product sales	Foreign R&D and domestic R&D	PROD GMM	Domestic R&D complements foreign R&D
Bin, 2008	Large and medium-sized manufacturing enterprises, 1996-2001	Labor productivity and number of patents	In-house R&D, foreign transfer, domestic transfer, and inter-industry R&D spillovers	PROD FE, RE	In-house R&D complements inter-industry R&D spillover and foreign transfer
Li, 2011	Large and medium-sized SOEs in high-tech industry, 1995-2004	Number of patents	R&D, domestic technology and foreign technology	PROD Negative binomial	Foreign technology complements R&D
Li and Wu, 2010	Large and medium-sized firms in 4 high-tech industries, 1995-2004	Number of patents	R&D, domestic technology and foreign technology	PROD Negative binomial	Foreign technology complements R&D

3.3. Empirical model and testing of complementarity

3.3.1 Definitions

A pair of economic activities is complementary if (1) adopting one does not preclude adopting the other one, and (2) the sum of the benefits of implementing each activity separately is not greater than the benefit of implementing both together. An equivalent understanding of the second condition is that the incremental return to implementing any one of the activities is greater if the other one is already implemented. A theorem states that if each pair of activities in a group is complementary, then implementing any subset of the activities in the group raises the incremental return to implementing the

¹⁵ For the methods of testing complementarity, see section 3.2.

remaining ones (Topkis, 1978). Complementarity between activities in economic models was by Vives (1990) and Milgrom and Roberts (1990b, 1995).

More formally, suppose there are two technology acquisition practices, R&D and TP, and Z is a vector of exogenous variables. If R&D and TP are discrete variables, they are complementary if the presence of one strategy (say, R&D) increases the marginal return of adopting the other strategy (TP) controlling for other effects. In other words, the objective function $f(R\&D, TP, Z)$ is supermodular meaning that the following inequality holds for all values of the other arguments of $f(\cdot)$ (Milgrom and Roberts, 1990a):

$$f(1, 1; Z) - f(1, 0; Z) > f(0, 1; Z) - f(0, 0; Z) \quad (3.1)$$

If R&D and TP are continuous variables, this inequality restriction implies that the incremental effect on the objective function of increasing one practice increases conditionally on increasing another practice:

$$\frac{\partial^2 f(R, T, Z)}{\partial R \partial T} > 0 \quad ; \text{ where } R \text{ stands for R\&D and } T \text{ for TP.} \quad (3.2)$$

Conversely, R&D and TP are substitutes if the inverse of inequality (3.1) or (3.2) holds.

Testing complementarity among activities in maximizing an objective function has been done in several empirical studies (Cassiman and Veugelers, 2006; Mohnen and Röller, 2003; Belderbos et al., 2008). This approach is known as the production function approach (PROD). It refers to a synergistic effect between activities which that will lead to a better performance in terms of a stated goal. Another approach to test complementarity, known as the correlation approach (CORR), consists in checking the sign of the correlation coefficient between strategies conditional on certain other determinants. In Table 3.1, methods adopted in testing complementarity are shown in column 5. The current study will focus only on the PROD. We shall consider two kinds of performance objectives: innovation output and total factor productivity (TFP). If there is complementarity between in-house R&D and technology purchase, it can show up in greater innovation output and indirectly in higher TFP levels through the effect of innovation output on TFP. Given the way in which innovation output and TFP are measured, we have to resort to different econometric models to test complementarity with respect to each of these two objectives.

3.3.2 Testing complementarity in terms of innovation output

Innovation output can refer to different kinds of innovation and can be measured in a qualitative or in a quantitative way. We shall consider two kinds of innovation output: new products and new processes. Based on the questionnaire, process innovation can be measured only by its incidence whereas product innovation will be measured by its incidence and its intensity. Hence for process innovation we specify a probit model, i.e. we observe a dichotomous variable $Proc_i$ which equals 1 when the firm claims to have introduced a new process in the period under review, and zero otherwise. The values one and zero correspond respectively to a positive and a negative value of a latent variable $Proc_i^*$, which is itself determined by innovation inputs and firm-specific variables:

$$Proc_i^* = \nu_b I_{bi} + \nu_m I_{mi} + \delta_b I_{bi} \ln r_{bi} + \delta_m I_m \ln r_{mi} + \delta_{bm} I_{bi} \ln r_{bi} I_{mi} \ln r_{mi} + \phi W_i^* + \eta_i \quad (3.3.1)$$

where $r_{b,i}$ and $r_{m,i}$ are the levels of innovation inputs (TP and R&D respectively), expressed in expenditure per employee, so that a marginal effect of an increase in their levels depends on the size of the firm.¹⁶ It is unreasonable to assume that the marginal effect of 1000 additional RMB spent on R&D or TP would be the same for large and small firms. W_i^* is a vector of exogenous variables that affect the probability of innovating. $\nu_b, \nu_m, \delta_b, \delta_m, \delta_{bm}$, and ϕ are coefficients to be estimated. η is a random error term due to measurement errors and omitted variables. Since R&D and TP have many zeros (around 60 per cent for R&D and 80 per cent for TP), we model them first as dichotomous variables ($I_{bi} = 1$ if TP is different from zero and $I_{mi} = 1$ if R&D is different from zero, and zero otherwise) and, if they are both present, we allow for complementarity or substitutability between them in their continuous variations. If δ_{bm} is positive (negative) and statistically significant, then there is complementarity (substitutability) between R&D and TP. Since there are only six cases¹⁷ where firms purchase technology without doing their own R&D, we cannot reasonably identify any complementarity or substitutability with the discrete variables.

¹⁶ Index b refers to “buy”, i.e. technology purchases, index m refers to “make”, i.e. own R&D.

¹⁷ Among these six cases, two are in the electronic equipment industry, two in electronic parts making industry, one in the garment and leather products industry and one in the metallurgical products industry.

For product innovation, we observe, on the one hand, a dichotomous variable Prod_i equal to one if a new product has been introduced on the market and zero otherwise, and on the other hand, a continuous variable Innosale_i , which measures the sales of new products per employee. Since this variable is only measured for firms that have introduced a new product on the market, OLS estimates would suffer from a potential selection bias. To correct for this bias, we shall specify a tobit type II model composed of a main equation of interest (3.3.2) and a selection equation (3.3.3):

$$\ln(\text{Innosale}_i) = \nu_b^o I_{bi} + \nu_m^o I_{mi} + \delta_b^o I_{bi} \ln r_{bi} + \delta_m^o I_{mi} \ln r_{mi} + \delta_{bm}^o I_{bi} \ln r_{bi} I_{mi} \ln r_{mi} + \phi^o W_i + \eta_i^o \quad (3.3.2)$$

$$\begin{aligned} \text{Prod}_i^* &= \nu_b^* I_{bi} + \nu_m^* I_{mi} + \delta_b^* I_{bi} \ln r_{bi} + \delta_m^* I_{mi} \ln r_{mi} + \delta_{bm}^* I_{bi} \ln r_{bi} I_{mi} \ln r_{mi} + \varphi W_i^* + \eta_i^*, \\ &\begin{cases} \text{Prod}_i = 1 & \text{if } \text{Prod}_i^* > 0; \\ \text{Prod}_i = 0 & \text{if } \text{Prod}_i^* \leq 0 \end{cases} \end{aligned} \quad (3.3.3)$$

where Prod_i^* in the selection equation (3.3.3) is a latent variable which indicates if a firm had any product innovation or not in the period under review depending on whether its value lies above the threshold zero or not. Innosale_i is only observed if $\text{Prod}_i = 1$. We assume that the error terms η_i^o and η_i^* follow a joint normal distribution with $\text{var}(\eta_i^*) = 1$, $\text{var}(\eta_i^o) = \sigma_2^2$, $\text{cov}(\eta_i^o, \eta_i^*) = \rho\sigma_2$. In order to identify the effects of the explanatory variables W_i and W_i^* , the latter will contain at least one extra exogenous variable not included in W_i . Due to the fact that the innovation output indicator is only available for the year 2002, the probit model (3.3.1) and the generalized tobit model (3.3.2) and (3.3.3) will be estimated on cross-sectional data.

3.3.3 Testing complementarity in terms of total factor productivity

In addition to looking at the effect of technology-sourcing strategies on innovation output, we will go one step further and also investigate whether there is a synergy between R&D and TP in promoting firms' productivity performance. We start from a general production function:

$$Y_{it} = g(\text{TFP}_{it})h(K_{it}, L_{it}, M_{it}) + \varepsilon_{it} \quad (3.4)$$

where Y_{it} stands for total sales, K_{it} , L_{it} and M_{it} represent respectively the inputs physical capital, labor and materials, TFP_{it} is the total factor productivity, which is driven by the innovation inputs, industry specificities and ownership characteristics, and ε_{it} is a random error term. Here we index all variables by subscripts i for firms and t for time, because now we have panel data. TFP is supposed to be a function of the innovation inputs $r_{b,it}$ (TP per employee) and $r_{m,it}$ (R&D expenditure per employee), other explanatory variables V_{it} (ownership dummies, export dummies and age of the firm), industry dummies (I_i) to capture differences in technological opportunities, and time dummies (T_t) to capture year-to-year fluctuations in productivity. We assume that the functions $g(\cdot)$ and $h(\cdot)$ are separable and that both are second-order approximations after a logarithmic transformation of (3.4).

After rewriting (3.4) in terms of labor productivity, so as to estimate directly the extent of scale economies, we obtain the labor productivity function (3.5):

$$\begin{aligned} \ln(Y_{it}/L_{it}) = & \gamma_0 + \beta_k \ln(K_{it}/L_{it}) + (\beta_l + \beta_k + \beta_m - 1) \ln L_{it} + \beta_m \ln(M_{it}/L_{it}) \\ & + 0.5\beta_{kk} (\ln(K_{it}/L_{it}))^2 + 0.5\beta_{mm} (\ln(M_{it}/L_{it}))^2 + \beta_{km} \ln(K_{it}/L_{it}) \ln(M_{it}/L_{it}) \\ & + I_{bit}(\alpha_b + \gamma_b \ln r_{bit} + 0.5\gamma_{bb} (\ln r_{bit})^2) + I_{mit}(\alpha_m + \gamma_m \ln r_{mit} + 0.5\gamma_{mm} (\ln r_{mit})^2) + I_{bit}I_{mit}(\alpha_{bm} + \gamma_{bm} (\ln r_{bit})(\ln r_{mit})) \\ & + \gamma_v V_{it} + \sum_j \gamma_j I_j + \sum_t \gamma_t T_t + \omega_i + \varepsilon_{it} \end{aligned} \quad (3.5)$$

As in equations (3.3) we model the effects of R&D and TP first as a step function with different levels of TFP for the observations where R&D or TP is present and secondly in a continuous way only for the cases where both are present. In (3.5) we have expressed R&D and TP in logarithms assuming constant elasticities. The disturbance term has two orthogonal components: the time-invariant individual effects ω_i , which are unobserved by the econometrician but known to the firm (such as managerial ability or organizational ability), and the idiosyncratic productivity shocks ε_{it} , which are unobserved by the econometrician and by the firm. We assume the idiosyncratic error term to be uncorrelated with past values of the explanatory variables.

The problem here is that the inputs, especially the traditional inputs, labor, capital and materials, but also the innovation related inputs $r_{b,it}$ and $r_{m,it}$ may be correlated with ω_i . The endogeneity of input practices makes OLS fail to generate consistent estimators. To tackle the endogeneity problem we use the system-GMM estimator (Arellano and Bond,

1991, Blundell and Bond, 1998).¹⁸ Taking the first differences of equation (3.5) will remove the unobserved individual effect ω_i , thus eliminating a potential source of omitted variable bias in the estimation. Then, the differenced variables that are not strictly exogenous are instrumented with all their available lagged levels (Difference GMM). However, lagged levels are poor instruments for first differences if the variables are close to a random walk (Holtz-Eakin, Newey, and Rosen, 1988; Arellano and Bover, 1995). Therefore, Blundell and Bond (1998) suggest adding another set of orthogonality conditions, namely between the levels of the error term and the first-differences in the exogenous variables under the assumption of stationarity. This is the idea behind System GMM.

3.4. Data and variables

The data used in our empirical analysis are from the World Bank Investment Climate Survey (ICS)¹⁹ - China 2003. The survey is conducted in 24 industrial cities and provides us with a wide range of information about the economic environment and activities of the firms. The majority of firms included in the ICS China 2003 are of small or medium size²⁰. After removing missing values, cleaning for outliers and removing the large size firms, we are left with 3332 observations of small and medium-sized firms from 18 cities and 10 manufacturing industries for the period 2000 to 2002²¹. Several aspects of firms'

¹⁸ We prefer to use the dynamic panel GMM approach to the proxy-based approach introduced by Olley and Pakes (1996). Ackenberg et al (2006) compare the two approaches and discuss their respective advantages and disadvantages.

¹⁹ See footnote 13.

²⁰ According to the National Bureau of Statistics of China, small-sized firms have fewer than 300 employees, medium-sized firms have between 300 and 2000 employees, and large size firms have more than 2000 employees. The classification is based on the number of long-term employees according to "The classification of small, medium and large Chinese manufacturing firms" from the National Bureau of Statistics of China: <http://www.stats.gov.cn/>. The large size firms included in the sample, after dropping missing values, represent about 3.5 per cent of the total sample (33 firms). We decided to drop these firms and look only at the small and medium-sized firms. Meanwhile, there are about 40 per cent of firms with fewer than 100 employees. It is interesting to look at their technological sourcing behavior separately since the t-tests in Table 3.2 and Table 3.4 show that their characteristics are significantly differently from those of other firms. In total, our sample is divided into three categories: firms with fewer than 100 employees (40.1 per cent), firms with a number of employees between 100 and 300 (30.37 per cent) and firms with more than 300 employees (29.53 per cent).

²¹ Firms with no information on financial outcomes are omitted. The service sector is not included because the innovation outputs are not reported. Furthermore, following Hall and Mairesse (1995), we keep only cases in which the capital-labor ratio is within three times the inter-quartile range (the difference between the 75 per cent value and the 25 per cent value) above or below the median. This removed 129 observations, or 2.1 per cent of the sample. The remaining sample is an unbalanced panel with 3332 observations for the period 2000 to 2002.

innovation activity are covered in the survey; such as the firms' innovative input strategies and innovation outputs. We deflate annual sales, profits, capital, materials and innovation expenditure to convert them into values expressed in year 2000 prices²².

3.4.1 Variables in the innovation equation

The dependent variable in the innovation equation (3.3.1) is a dichotomous variable equal to 1 if the firm claims to have had either a product or a process innovation in the years 2000 to 2002. In equation (3.3.2) the dependent variable is the log of sales of new products per employee. There are two categories of variables that might affect the probability of having a successful innovation and the intensity of innovative sales.

The first category captures firm specificities. With more profits in previous periods, firms have more cash available and are therefore more likely to invest in innovation and be successful innovators (Katrak, 1997). PROFIT per employee is the average ratio of profit (before tax) per employee from 2000 to 2002. CAPITAL per employee, which is the average capital/labor ratio from 2000 to 2002, serves as an indicator of the capital intensity, but it also to some extent reflects the size of a firm. Larger firms are expected to have more resources to allocate to innovation activities, which leads to better innovation performance. Company ownership can be a crucial variable in innovation performance in the case of China, as it affects the motivation to innovate and the continuity of business strategy. State-owned enterprises (SOEs) are usually reluctant to undertake changes. However, with investment and tax incentives from the government, they might have more resources to carry out innovation activities. So the effect of SOEs on innovation output is ambiguous. Foreign-controlled firms tend to concentrate their research and development in their home countries (OECD, 2003). A negative sign is expected. SOE and FOREIGN indicate respectively state and foreign ownership. The dummy EXPORT indicates if firms have positive exports in 2002. On the one hand, the point of learning-by-exporting suggests that technology flows from international buyers help to improve the performance of exporters (Salmon and Shaver, 2005; Liu and Zou., 2008). Furthermore, fierce competition on the international market stimulates firms to be innovative. On the other hand, especially in the case of China, exporting firms compete successfully in the international market by relying on the price advantage of already-existing products due to the relatively low material and labor costs. This might inhibit

²² For the annual sales and profits, we use the wholesale price deflators at the industry level. For capital, material and innovation expenditure, the industry input deflators are used (Chinese Bureau of Statistics, 2000-2003).

innovation, especially product innovation. So the sign of EXPORT is ambiguous. AGE is calculated as the number of years evolved since the enterprise started production up to 2002. Young firms are expected to be more dynamic and innovative all other things equal (Katrak, 1997), and therefore a negative effect is expected. Innovation activities tend to be relatively more intensive in the technologically more advanced industries, such as pharmaceuticals, electrics and electrical equipment, and electronics. Industry specificities are controlled for by industry dummies.

The second category of explanatory variables is the set of innovation inputs. The survey contains information on two technology-sourcing strategies. Firms are asked to report their annual in-house R&D expenditure. In-house R&D spending comprises capital, labor and design costs associated with research and development. The other way for firms to increase their technological expertise is to buy technology directly from external channels, on the domestic or the international market. Technology purchasing is defined in the questionnaire as the amount that firms spend on purchasing technology externally. The two variables are respectively denoted by R&D and TP. Both are measured in average spending per employee in 2000–2002. More investment in in-house R&D and external technology purchasing will strengthen the firms' technological capability and contribute to raising their innovation output. We expect both marginal effects to have a positive sign. The sign of the interaction term of R&D and TP indicates their complementarity or substitutability. Dummy variables R&D_PRI, R&D_UNI, and R&D_FIRM are equal to 1 if firms have any R&D cooperation with public research institutes, universities, or other firms. The Chinese government has strongly encouraged Public Research Institutes (PRIs) and universities to create more effective links with industry since the 1980s. In 2004, about one-third of large and medium-sized companies' R&D spending went to universities and PRIs as contracted R&D (National Bureau of Statistics of China, 2006). We use these three variables as proxies for technological opportunity. Any form of co-operation constitutes an information source for new technologies and could lead to innovativeness. The benefits drawn from co-operative activities might only show up in the probability of innovation but not in new product sales, since most of the innovations carried out in universities and research institutes focus on basic science research that will not be immediately commercialized in the market.

Additional variables are included in the selection equation (3.3.3) in order to avoid identification problems. These variables are expected to influence the occurrence of product innovation, but not the intensity. In reality, such variables are difficult to define (Puhani, 2000; Vella, 1998). City dummies will be used here as proxies for the location of a firm. In China, being located in a developed industrial city (such as in the coastal area) may provide firms with greater policy-oriented opportunities to undertake innovation activities. However, location may not affect the intensity of innovation, which depends rather on variables reflecting the market structure (as shown by Sasidharan and Kathuria, 2011).

3.4.2 Variables in the production function

In the production function, the dependent variable is PRODUCTIVITY. It is measured in sales per employee. The three conventional inputs are CAPITAL, measured as the total book value of fixed assets, LABOR, measured as the number of full-time employees, and MATERIAL, measured as the costs of raw materials, energy and other related costs reported by the firm²³. The innovation inputs R&D and TP and their interaction will also enter the productivity equation as endogenous variables. We control for several variables (FOREIGN, SOE, and EXPORT) that capture the firms' competitiveness and technological capability. Foreign-owned firms are characterized by higher capital intensity, high quality of human capital and efficient management. Many previous studies suggest that foreign-owned firms are more productive (Globerman et al., 1994; Doms and Jensen, 1998; Kimura and Kiyota, 2007). State-owned enterprises (SOEs) are usually characterized by redundant workers and inefficient management. As we can see from Table 3.2, SOEs are mostly medium-sized firms (hence above the sample average with respect to the number of employees) while their productivity is below the sample average. They are not motivated to perform efficiently because the local government takes full responsibility for their production and profit. For this reason, we expect SOEs to have a negative effect on the productivity performance. EXPORT activities are expected to enhance economic growth and improve the productivity of involved firms (Beckerman, 1962; Bhagwati, 1988). Firms participating in international markets are exposed to more intense competition. More vigorous competition exerts discipline on firms. It therefore tends to strengthen their efficiency, and we expect a

²³ The capital and material inputs are logarithmically transformed and expressed in 1000 RMB per employee.

positive effect. We also control for industry and year specificities by using industry and year dummies.

3.4.3 Descriptive statistics

Tables 3.2 to 3.4 provide descriptive statistics on the conventional inputs, the productivity performance, the technology sourcing and the control variables across industries. As Table 3.2 shows, high-tech industries such as electronic equipment, household electronics and biotechnology have a higher capital/labor ratio, are more productive and more active in collaborative research. Enterprises in household electronics and garments are more likely to sell their products abroad and to be foreign-owned. Firms with fewer than 100 employees are on average younger, less collaborative in research, less capital intensive, less often foreign- or state-owned, less export-oriented and less productive. Table 3.3 provides the descriptive statistics across industries for SOEs. Except for the transportation equipment industry, SOEs have lower labor-productivity level than the other firms in the corresponding industry confirming the OECD (2007) report. In contrast, SOEs are more capital-intensive and bigger (in terms of number of employees). They are more numerous in electronic parts, auto parts, metallurgical products and the garment industry. They are less likely to export and their average age is 28 years, which is almost twice the average age of the whole sample. They are more likely to collaborate in research. Notice that almost half of the SOEs in the biotechnological industry claim to have R&D cooperation with public research institutions.

Table 3.4 presents the innovation outputs and inputs of Chinese small and medium-sized manufacturing firms. Approximately 46 per cent of the firms claim to have introduced a new product and 25 per cent have introduced a new process in the period under review. Technology intensive industries such as electronics and biotech are more likely to be innovators, and they also perform better in terms of new product sales as shown by column four in Table 3.4. It should be noted that the product and process innovations in developing countries are not conventionally defined as new to the market, but rather as new to the firm.

Table 3. 2 Firm average across industries (full sample)

Industry	N. obs	Productivity	Capital	Material	Labor	SOE dummy	Foreign dummy	Export dummy	Age	R&D_UNI	R&D_PRI	R&D_FIRM
Garment & leather	778	3.871	3.091	3.059	4.953	0.090	0.193	0.391	12.772	0.042	0.035	0.063
Electronic equipment	375	5.044	3.851	4.080	4.957	0.200	0.224	0.195	9.523	0.237	0.187	0.205
Electronic parts	614	4.210	3.690	3.321	4.860	0.259	0.137	0.176	16.614	0.155	0.137	0.164
Household electronics	128	4.525	3.825	3.273	5.216	0.047	0.367	0.445	11.461	0.172	0.102	0.188
Auto & auto parts	734	4.344	3.716	3.560	5.261	0.228	0.113	0.108	16.634	0.082	0.105	0.178
Food processing	144	4.483	3.624	3.603	4.898	0.250	0.146	0.069	15.708	0.188	0.181	0.125
Chemical product	134	4.287	3.935	2.980	4.865	0.261	0.045	0.104	14.985	0.082	0.194	0.157
Biotech products	60	4.764	4.106	2.986	4.901	0.200	0.050	0.067	11.400	0.417	0.417	0.133
Metallurgical product	327	3.601	3.534	2.601	4.765	0.312	0.092	0.064	17.294	0.055	0.086	0.150
Transportation equipment	38	3.100	2.565	1.887	4.216	0.237	0.079	0.000	11.816	0.000	0.000	0.132
SOE firms ²⁴	671	3.845	4.066	2.901	5.666	1.000	0.000	0.107	28.261	0.142	0.137	0.168
Non-SOEs	2661	4.313	3.439	3.402	4.808	0.000	0.171	0.225	11.079	0.107	0.107	0.139
Employees < 100	1304	3.972	3.215	3.097	3.743	0.112	0.079	0.080	10.888	0.080	0.070	0.110
Employees ≥ 100 & < 300	1026	4.361	3.533	3.455	5.126	0.151	0.188	0.252	12.901	0.112	0.110	0.148
Employees ≥ 300	1002	4.393	4.054	3.409	6.443	0.369	0.215	0.306	20.967	0.161	0.172	0.187
Total	3332	4.219	3.565	3.301	4.981	0.201	0.153	0.201	14.539	0.114	0.113	0.145

Notes: Productivity is in logarithm of sales (in 1000 RMB) per employee;
Capital and material are also logarithmically transformed and in 1000RMB/employee;
Labor is the logarithm of the number of employees in the firm;
R&D_UNI: dummy variable =1 if a firm reports co-operation with universities;
R&D_PRI: dummy variable =1 if a firm reports cooperation with public research institutes;
R&D_FIRM: dummy variable =1 if a firm reports co-operation with other firms.

²⁴ t-tests have been used to test the differences in means between SOEs and Non-SOEs for our main variables. The differences are significant (at 90 per cent level) for all variables in table 3.2 except for R&D_UNI, R&D_RES and R&D_FIRM. Similar t-tests have been conducted to compare the means of main variables for different size classes. The differences are always significant (at 90 per cent level) for firms with fewer than 100 and those with between 100 and 300 employees. For firms with 100 to 300 and above 300 employees, the only two variables where the differences are not significant at 90 per cent level are MATERIAL and R&D_UNI.

Table 3. 3 Firm average across industries (for SOEs)

Industry	N. obs	Productivity	Capital	Material	Labor	Export dummy	Age	R&D_UNI	R&D_PRI	R&D_FIRM
Garment & leather	70	3.376	3.814	2.439	5.141	0.257	26.014	0.029	0.029	0.057
Electronic equipment	75	4.513	3.833	3.578	5.456	0.120	18.600	0.280	0.267	0.240
Electronic parts	159	3.808	4.094	2.823	5.520	0.164	28.843	0.189	0.214	0.257
Household electronics	6	2.383	4.717	1.762	6.159	0.000	3.000	0.000	0.000	0.000
Auto & auto part	167	4.068	4.351	3.312	6.258	0.072	33.413	0.126	0.072	0.137
Food processing	36	3.818	4.176	2.851	5.181	0.000	35.833	0.083	0.028	0.083
Chemical products	35	3.964	4.168	2.911	5.541	0.114	24.971	0.029	0.057	0.228
Biotech products	12	4.034	4.351	2.832	5.438	0.000	31.500	0.333	0.500	0.083
Metallurgical product	102	3.459	3.758	2.413	5.684	0.029	27.676	0.127	0.147	0.117
Transportation equipment	9	3.225	3.970	1.138	5.285	0.000	22.000	0.000	0.000	0.333
Total	671	3.845	4.066	2.901	5.666	0.107	28.261	0.142	0.137	0.168

Notes: Productivity is in logarithm of sales (in 1000 RMB) per employee;

Capital and material are also in logarithmically transformed and in 1000RMB/employee;

Labor is the logarithm of the number of employees in the firm;

R&D_UNI: dummy variable =1 if a firm reports co-operation with universities;

R&D_PRI: dummy variable =1 if a firm reports co-operation with public research institutes;

R&D_FIRM: dummy variable =1 if a firm reports co-operation with other firms.

It has been postulated that new and dynamic industries in developing countries can most readily catch up (Gerschenkron, 1962). Under the R&D, TP, R&D and TP headings we report the observed incidences²⁵ and corresponding expenditure statistics. As is shown in Table 3.4, the electronic equipment, auto and auto parts and biotech industries spend more on technology acquisition, both internally and externally, than traditional industries such as chemicals, garment and leather and food processing. The relatively lower innovation efforts might explain why most Chinese firms in low-tech industries have not been able to catch up with technology advances, as argued by Fu and Gong (2010).

²⁵ The percentage of firms that claimed to have positive expenditures of R&D and TP in the period under review.

Table 3. 4 Descriptive statistics of innovation inputs and outputs across industries (mean values in 2002)

Industry	Innovation		New product sales per employee	R&D		TP		R&D & TP	
	Products	Process		Incidence	Expenditure	Incidence	Expenditure	Incidence	Expenditure
Garment & leather	0.246	0.123	2.344	0.264	-0.186	0.078	-0.180	0.074	0.256
Electronic equipment	0.643	0.384	3.123	0.616	0.746	0.256	-0.001	0.240	0.749
Electronic parts	0.542	0.316	2.116	0.485	0.196	0.223	0.000	0.214	0.362
Household electronics	0.648	0.438	2.625	0.581	-0.031	0.256	-0.042	0.256	1.212
Auto & auto part	0.527	0.260	2.151	0.482	0.079	0.215	-0.167	0.215	0.655
Food processing	0.553	0.261	2.420	0.396	-0.233	0.229	-0.210	0.229	0.341
Chemical product	0.425	0.224	1.365	0.304	0.005	0.217	-0.089	0.217	0.245
Biotech products	0.700	0.222	2.407	0.600	0.693	0.350	0.288	0.350	1.039
Metallurgical product	0.385	0.220	1.530	0.312	-0.072	0.128	-0.199	0.119	0.443
Transportation equipment	0.143	0.086	0.424	0.154	0.484	0.077	0.031	0.077	0.030
SOE firms ²⁶	0.563	0.328	1.294	0.485	-0.142	0.203	-0.247	0.194	0.440
Non-SOEs	0.440	0.231	2.761	0.405	0.155	0.179	-0.071	0.175	0.502
Employees < 100	0.353	0.194	2.970	0.278	0.143	0.106	0.005	0.101	0.229
Employees ≥ 100 & < 300	0.476	0.242	2.852	0.411	0.103	0.192	-0.094	0.183	0.557
Employees ≥ 300	0.608	0.331	1.635	0.614	0.024	0.275	-0.262	0.272	0.753
Total	0.464	0.251	2.278	0.422	0.094	0.184	-0.107	0.178	0.489

Note: Innovation (products/process): dummy variable equal to 1 if a firm has introduced a new product (process) in the period of 2000 to 2002;

New product sales: sales of new product per employee, in logarithms;

R&D expenditure (RD) and technology purchases (TP) are expressed in 1000 RMB per employee, in logs; R&D&TP is the product of R&D and TP.

The lack of efficiency of Chinese SOEs is also shown in the innovation input and output data. The proportion of firms that do in-house R&D is higher for SOEs than for the total sample and the same goes for technology purchasing. As a result, the innovation propensities in terms of products and processes are above the overall averages. However, the intensities of R&D and TP expenditures per employee are lower for SOEs than for the overall sample and the average value of new product sales per employee, which takes

²⁶ t-tests have been used to test the differences in means between SOEs and Non SOEs for our main variables. The differences are significant (at 90 per cent level) for all variables in table 3.4 except for TP. Similar t-tests have been conducted to compare the means of main variables for different size classes. The differences are always significant (at 90 per cent level) for firms with 100 to 300 and above 300 employees. For firms with fewer than 100 and those between 100 and 300 employees, the only variable where the differences are not significant at 90 per cent level is PROCESS.

into account the relative level and the market success of innovation, is substantially below the overall sample average. A similar pattern holds in terms of firm size. Enterprises with fewer than 100 employees are lower in terms of engaging in R&D and TP and introducing new products and processes, but higher in R&D, TP and product innovation intensities compared with other two groups (firms with 100 to 300 employees and firms with more than 300 employees).

3.5 Empirical results

We now turn to the results of the econometric analysis regarding how the two technology-sourcing strategies, R&D and TP, affect the innovation and productivity performances of small and medium-sized Chinese manufacturing firms, and the questions of whether they are substitutes or complements. We have divided the sample into three groups, the set of firms with fewer than 100 employees (very small-sized firms), the set of those with more than 100 and fewer than 300 employees (small-sized firms), and the set of those with more than 300 employees (medium-sized firms), because there are some clear differences between the three groups.

3.5.1 The role of R&D and TP in stimulating innovation

Table 3.5 presents the marginal effects of the regressors in the Probit model (equation 3.3.1) and the tobit type II model (equations (3.3.2) and (3.3.3)). The observed frequencies of R&D performers and technology purchasers are 42 per cent and 18 per cent respectively, and only six firms that bought knowledge from outside did not perform their own R&D. We had difficulties identifying a separate intercept for firms with their own R&D and external technology purchases and therefore did not introduce the interaction of the two dummies in the model.

Table 3. 5 Estimation results of innovation output (probit for process innovation, tobit type II for product innovation), marginal effects

VARIABLES	<100 employees			>=100 employees		
	Probit	Tobit type II		Probit	Tobit type II	
	Process innovat.	New product sales/person	Product innovat.	Process innovat.	New product sales/person	Product innovat.
	(1)	(2)	(3)	(4)	(5)	(6)
I _m	0.108 (0.068)	0.439*** (0.127)	0.225*** (0.083)	0.112** (0.048)	0.296*** (0.164)	0.258*** (0.056)
I _b	-0.013 (0.088)	0.266* (0.147)	-0.047 (0.125)	-0.099** (0.050)	0.252* (0.141)	0.020 (0.076)
I _m ln(R&D/labor)	0.017 (0.024)	0.064 (0.042)	-0.016 (0.032)	0.029 (0.018)	0.201*** (0.047)	0.037* (0.022)
I _m ln(R&D/labor) ² /2	0.002 (0.019)	0.002 (0.003)	0.039 (0.026)	-0.006 (0.012)	0.014*** (0.004)	0.002 (0.015)
I _b ln(TP/labor)	0.080 (0.057)	0.119 (0.100)	-0.036 (0.067)	0.027 (0.031)	0.149*** (0.074)	0.061 (0.046)
I _b ln(TP/labor) ² /2	0.032 (0.055)	0.004 (0.004)	0.017 (0.079)	-0.002 (0.026)	0.008 (0.014)	-0.014 (0.032)
I _{bm} ln(R&D/labor) *ln(TP/labor)	-0.029 (0.056)	0.005 (0.003)	0.009 (0.053)	0.023 (0.029)	0.016*** (0.004)	0.023 (0.034)
SOE	-0.057 (0.056)	0.090 (0.128)	0.105 (0.094)	0.173*** (0.057)	-0.067 (0.135)	0.146** (0.061)
FOREIGN	0.073 (0.089)	0.304** (0.126)	0.083 (0.106)	0.019 (0.050)	-0.041 (0.125)	-0.042 (0.062)
AGE	-0.002 (0.002)	-0.012*** (0.004)	-0.006** (0.003)	-0.001 (0.001)	-0.016*** (0.004)	-0.001 (0.002)
CAPITAL/labor (avg 2000-2002)	0.000 (0.000)	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.000)	-0.001 (0.001)	-0.001 (0.000)
PROFIT/labor (avg 2000-2002)	-0.001* (0.001)	0.003*** (0.001)	0.001 (0.001)	0.000 (0.000)	0.017*** (0.001)	0.007*** (0.002)
EXPORT	0.042 (0.084)	-0.152 (0.133)	-0.000 (0.102)	0.140*** (0.052)	-0.139 (0.118)	0.037 (0.060)
R&D_UNI	0.203** (0.098)	0.616*** (0.124)	0.197* (0.110)	0.111* (0.058)	0.076 (0.130)	0.074 (0.067)
R&D_PRI	-0.017 (0.073)	0.636*** (0.120)	0.038 (0.109)	0.059 (0.056)	0.099 (0.127)	0.048 (0.068)
R&D_FIRM	0.069 (0.072)	0.688*** (0.112)	0.390*** (0.088)	0.128** (0.051)	0.370*** (0.134)	0.285*** (0.052)
ρ		0.079			-0.765***	
σ _η		1.233			1.751	
Nb observations	435	159	435	680	372	680

***p-value 0.01, **p-value 0.05, *p-value 0.1. Industry dummies are included. City dummies are included in the probit for process innovation and in the selection equation for the product innovation. New product sales per employee is in logarithms. I_b indicates that R&D>0, I_m indicates that TP>0, I_{bm} indicates that both R&D and TP are positive.

In columns (1) and (4) we report the marginal effects of the explanatory variables on the incidence of process innovations, in columns (3) and (6) the marginal effects on the incidence of product innovations. In columns (2) and (4) we report the marginal effects of the explanatory variables on the unconditional expectation of new product sales per employee. Calculations of unconditional marginal effects/elasticities are based on (3.a10)-(3.a14) in appendix A. When computing the marginal effects of I_b or I_m we take into account all the terms where these two dummies appear (i.e. four terms in total). For I_mln(R&D/labor) and I_bln(TP/labor), we include in the computation of the elasticities the effects of the square term and the interaction term. The marginal effects of I_mln(R&D/labor)²/2 and I_bln(TP/labor)²/2 represent second-order derivatives and the marginal effect of I_mln(R&D/labor)*I_bln(TP/labor) represents the second-order cross derivative of the unconditional expectation of new product sales/employee. Standard Errors are computed using the Delta method.

In Table 3.5 we report the marginal effects of the explanatory variables for the probit regression for process innovation and the selection equation for product innovation and the marginal effects on the unconditional expected value of new product sales per employee. In Appendix 3A we derive the marginal effects of the regressors on the conditional (equation 3.a7) and unconditional expectations of new product sales per employee (equations (3.a10)-(3.a14)). When computing the marginal effects of dummy I_b or I_m we take into account all the terms where these two dummies appear (i.e. four terms in total). For $I_m \ln(R\&D/labor)$ and $I_b \ln(TP/labor)$, we include in the computation of the elasticities the effects of square term and the interaction term. The marginal effects of $I_m \ln(R\&D/labor)^2/2$ and $I_b \ln(TP/labor)^2/2$ represent second-order derivatives and the marginal effect of $I_m \ln(R\&D/labor) * I_b \ln(TP/labor)$ represents the second-order cross derivative of the unconditional expectation of new product sales/employee. Standard Errors are computed using the Delta Method²⁷.

R&D is found to have a significant positive effect on process innovation only for firms with more than 300 employees. Firms that do R&D have a 21.3 percentage-points higher incidence of process innovation than those that do no R&D (coefficient of I_m)²⁸. Our data do not allow us to conclude anything regarding the marginal effect of a quantitative increase in R&D on process innovation, except for small firms where a 10 per cent increase in R&D per employee increases the probability of innovating by 0.7 percentage points. Technology purchasing has a negative and significant effect on process innovation, again only in a certain size class, this time medium-sized firms: technology purchasing firms have there on average a 15.8 percentage points lower incidence of process innovation than non-technology purchasing firms. For all other firms we cannot conclude anything about how TP affects process innovation. Our two sources of technology have a clearer effect on product innovation. In very small firms (fewer than 100 employees), R&D performing firms have a 22.5 percentage points higher probability of being product innovators and a 43.9 per cent higher sales of new products per employee than non-R&D performing firms. In medium-sized firms the incidence is 35.7 percentage points higher, and the sales of new products per employee are 54 per cent higher for R&D firms than for non-R&D firms. In small firms (between 100 and 300

²⁷ The Delta method is based on the first order approximation around the mean. For more details, see Oehlert (1992).

²⁸ When computing the marginal effects of I_b or I_m we take into account all the terms where these two dummies appear (i.e. four terms in total).

employees), these magnitudes are not precisely estimated, but the new product sales elasticity with respect to R&D is 0.404. Technology purchasing has also a positive effect on product innovation. In very small firms, TP firms have on average a 26.6 percent higher sales figure per employee than non-TP firms; small TP firms are on average 32.4 percentage points more likely to innovate in products than non-TP firms, and their sales per employee are 86.1 per cent higher, which, however, declines by 2.1 per cent as TP expenditure per employee increase by 10 percent (coefficient of $I_b \ln(TP/labor)$)²⁹; and finally in medium sized firms new product sales per employee rise by 3.8 per cent as TP per employee increases by 10 per cent. The only significant sign of complementarity between R&D and TP is visible for small firms, where the elasticity of new product sales per employee with respect to R&D increases by 0.22 per cent as technology purchasing increases by 10 per cent.³⁰ The synergy between own R&D and external technology purchasing, at least as it is evident in small Chinese manufacturing firms (between 100 and 300 employees), is in line with the argument of absorptive capacity (Cohen and Levinthal, 1990) and the results reported by Li and Wu (2010), Liu and White (1997), Liu and Buck (2007) and Liu and Zou (2008).

Among the control variables, characteristics such as being an exporter, a young firm, or a foreign-owned firm, a firm that co-operates in R&D positively affect the probability or the intensity of innovating. Exporting firms with 100 to 300 and more than 300 employees have a 16 and 14 percentage-points higher probability of process innovation. Old firms are expected to be less dynamic and innovative (Katrak, 1997). Indeed, they have 1.2 to 2.7 percentage-points lower sales of new products per employee in very small and small-sized firms. Foreign-owned firms with fewer than 100 employees have a 30 percentage points higher product innovation intensity. Due to the high costs and uncertainties connected with innovation, firms with profits are more likely to have the adequate financial resources to innovate. An increase of 1000 RMB in profit per employee increases by 0.3 percentage points the sales of new products per employee for firms with fewer than 100 employees and by 1.7 and 1.8 percentage points for small and medium-sized firms. State-owned enterprises have a 21 percentage-points higher probability to innovate in processes if they have more than 300 employees. They

²⁹ When computing the marginal effects of $I_m \ln(R\&D/labor)$ and $I_b \ln(TP/labor)$, we include in the computation of the elasticities of the square term and the interaction term.

³⁰ As Ai and Norton (2003) pointed out, complementarity should be based on a positive sign of the cross-elasticity and not the interaction term alone.

probably benefit from more financial and policy support from government. R&D collaborations with other firms, public research institutes and universities increase the probability to innovate and the intensity of product innovations especially for the very small firms (see Boeing, Mueller and Sandner, 2012). Those with fewer than 100 employees that benefit from any kind of R&D collaboration have a 60 percentage points higher sales of new products per employee. For firms with 100 to 300 employees, it is mostly collaborations with other firms and universities that affect the innovation intensity, increasing it by 59.6 and 53.5 percentage points. Collaborations with universities seem to decrease sales of new products per employee by 36.3 per cent in medium-sized firms.

3.5.2 The role of R&D and TP in promoting productivity

We now go a step further and examine the issue of complementarity or substitutability between in-house R&D and technology purchasing in terms of achieving a better productivity performance, since in the end innovation serves to improve productivity. Table 3.6 presents the results of the productivity equation (3.5) obtained using ordinary least squares (OLS) and the system GMM method. The system GMM exploits the orthogonality conditions between the first differences in the error term and the explanatory variables in levels lagged by one period, once for 2002 and once for 2001, and the orthogonality conditions between the error terms in levels and the lagged first differences of the explanatory variables. Hence in total there are 85 orthogonality conditions, 29 estimated coefficients, and consequently 56 overidentifying restrictions³¹. The OLS estimates are likely to be inconsistent because of the endogeneity of the conventional inputs and the innovation strategy variables. They are only shown as a benchmark. In the presence of a positive productivity shock we expect firms to increase

³¹ The number of orthogonality conditions equals the number of instruments used for the endogenous variables plus the number of pre-determined variables (used as their own instruments). In the GMM case, 14 variables are considered to be endogenous (the first fourteen independent variables in the table). We consider the first differences in the error term of the productivity equation to be orthogonal to the one and two-period lagged levels of the endogenous variables for the year 2002 and to the one-period lagged levels of the endogenous variables for the year 2001 (remember, we have no data prior to 2000). That makes 42 orthogonality conditions so far. As to the level of the error term, we consider it to be orthogonal to the first differences in the endogenous variables for 2002 and for 2001. That makes 28 additional orthogonality conditions (14 for each year). So, in total the system GMM exploits 70 orthogonality conditions to instrument for the endogenous variables, plus 15 orthogonality conditions using the predetermined variables of our model (the time, industry, ownership and exporting status dummies) in the first difference equations, which makes a grand total of 85 orthogonality conditions. The number 56 in the Hansen overidentification test equals the total number of orthogonality conditions (85) minus the number of estimated parameters (29).

their inputs, but the existence of adjustment costs for labor and capital will have them increase materials more than the two quasi-fixed inputs. Hence we would expect an upward bias in the estimate of the output elasticity of the inputs, more for materials than for labor and capital. R&D is probably more quasi-fixed than technology purchases and hence we expect a stronger upward bias for the latter than for the former. The directions of bias are partly confirmed by our estimates. Yet, the OLS estimates are not very different from the GMM estimates, which is a sign that the latter are not unreasonable. Our interpretation will be based on the system GMM estimation, which tackles the endogeneity problem. The instruments used in the GMM estimation are acceptable by the Hansen test of overidentifying restrictions, which is only significantly different from zero at a p-value of 38 (resp. 16) per cent for firms with fewer (resp. more) than 100 employees. The Difference-in-Hansen test also accepts the 28 additional orthogonality conditions of the level equations that differentiate the System GMM from the First-difference GMM estimates.³²

We have chosen a translog approximation to a general production function in the conventional inputs (the $h(\cdot)$ function in equation (3.4)) as well as a translog approximation of the total factor productivity expression in the two technology variables (the $g(\cdot)$ function in equation (3.4)). We have normalized the conventional inputs, capital and material, and the technology inputs, R&D and TP, by labor and introduced a separate labor term to capture the departure from constant returns to scale with respect to all the inputs.³³ The point of approximation is around unit values of the input/output ratios, which is out of the sample for the conventional inputs (see Table 3.2) but quite reasonable for the technology inputs (see Table 3.4). We have also accounted for the fact that many firms have no R&D or no technology purchase by including dummy indicators for these two variables and by interacting these dummy variables with their respective amounts when they are positive.

We cannot reject the null hypothesis of constant returns to scale (the $\ln(\text{labor})$ coefficient is not significantly different from 0). Capital and material are substitutes. In the bottom subpanel of Table 3.6, we report the output elasticities of physical capital, materials,

³² The two-step system GMM performed in STATA 11, using the `xtabond2` command, automatically corrects the standard errors for heteroskedasticity and autocorrelation (Roodman, 2006).

³³ By dividing all the inputs by labor and dividing output by labor, we have imposed that the second-order parameters of the translog approximation sum up to zero and the first-order terms sum up to 1, so as to impose constant returns to scale. We have then allowed the sum of the first-order terms to deviate from 1 by allowing for a labor first-order term to appear on the right-hand side.

R&D and TP evaluated at the means of the variables³⁴. The elasticities for capital are quite reasonable, around .12 to .18 for capital and .57 to .62 for material.

The results in Table 3.6 show that firms with in-house R&D/employee at its mean value and no TP have a 29 (resp 18 per cent) higher labor productivity than firms with no R&D in the small (resp. medium-sized firms and no significant difference in labor productivity for very small firms (coefficients of I_m). In contrast the effect of technology purchases is visible mainly in very small firms and small firms, but not in medium-sized firms. With technology purchases are at their mean value and no R&D, very small (resp. small) firms have a 69 (resp. 39) per cent higher labor productivity than firms with no technology purchasing. Medium-sized firms show no significant difference in labor productivity between TP and non-TP firms. For firms that do both R&D and TP, labor productivity is significantly lower than for firms that do neither of them. In this sense, the two means of knowledge accumulation are at odds with each other. Since their respective effect on innovation (product and process) is generally positive, the average negative effect on labor productivity for firms that pursue both strategies must be due to some excessive cost, a possible duplication of knowledge acquisition, or some correlation of those activities with other associated characteristics, such as lack of experience or age of the firm. For instance, one could imagine that young, non technology-based firms, are less efficient because they lack know-how or technological capabilities, which they try to acquire by all possible means from inside or outside the firm.

The elasticity of output with respect to R&D (for R&D-performing firms) shows significance only for small firms, where we obtain an elasticity of 0.11, which is quite consistent with the elasticities reported in the literature (see Hall, Mairesse, Mohnen, 2010). The elasticity of output with respect to TP (for firms with TP) is significant at 0.10 (coefficient of $I_b \ln(\text{TP}/\text{labor})$) in medium-sized firms and not significant elsewhere. A complementarity between R&D and TP actually shows up in very small firms (coefficient of $I_{bm} \ln(\text{R\&D}/\text{labor})\ln(\text{TP}/\text{labor})$), while in the other firms the cross-elasticity of output with respect to R&D and TP is not significant. This means that in very small firms the returns from investing in one source of knowledge, R&D or technology purchasing, increases with the investment in the other source. In that sense the two strategies are

³⁴ When the marginal effects were computed, we include the elasticities of the square term and the interaction term. For computing the marginal effects of $\ln(\text{capital}/\text{labor})$ and $\ln(\text{material}/\text{labor})$, the square term and the interaction term are also accounted.

complements. As for the control variables the results are not surprising. In China, the majority of foreign-invested firms are in the high-tech industry and in general characterized by the higher average technical efficiency compared with domestic firms (Fu and Gong, 2010). As expected, foreign-owned firms are more productive than the reference category of firms in terms of ownership structure, i.e. domestic, non-state-owned firms. In contrast to foreign firms, SOEs tend to be less productive compared with firms with other ownership structures. This evidence reflects the inefficiency of Chinese SOEs. This finding is consistent with studies in other developing countries (Braga and Willmore, 1991). Exporting firms in China, at least those with more than 300 employees, are more productive than non-exporting firms. This may indicate that the pressure on international markets enables firms to foster their productivity or that the higher productivity enables firms to export.

We must be cautious when we compare our results with others in the literature. Hu et al (2005) found complementarity between domestic R&D and technology transfer. But their results are based on large and medium size Chinese enterprises which probably involve a different pattern of innovation sourcing strategies. Bönte (2003) and Belderbos et al (2008) showed to a complementarity between internal (i.e. in-house) and external (i.e. contracted-out) R&D in West-Germany and the Netherlands respectively. But our study is not comparable to theirs because our measure of purchased technology relates to the purchase of existing technology, from domestic or foreign sources, and not to the execution of R&D outside of the firm's R&D facilities. We investigate the complementarity not between ways of performing R&D but between R&D and the purchase of existing technology. Fikkert (1993) and Basant and Fikkert (1996) found substitutability between R&D and TP for Indian firms, but that was in a regime where there were controls on the external sourcing of technology, whereas in the period that we are examining Chinese firms were actually encouraged to import technology.³⁵

³⁵ We thank an anonymous referee for this remark.

Table 3. 6 Estimation results of the productivity equation

	<100 employees		>=100 & <300 employees		>=300 employees	
	OLS	GMM	OLS	GMM	OLS	GMM
ln(capital/labor)	0.084*** (0.016)	0.182*** (0.049)	0.131*** (0.023)	0.082** (0.038)	0.183*** (0.027)	0.079** (0.032)
[ln(capital/labor)]²/2	0.001 (0.011)	-0.010 (0.022)	-0.009 (0.027)	0.019 (0.019)	0.019 (0.031)	0.029 (0.060)
ln(labor)	0.042 (0.035)	0.026 (0.073)	0.059 (0.071)	-0.000 (0.093)	-0.037 (0.042)	0.128 (0.104)
ln(material/labor)	0.657*** (0.013)	0.619*** (0.025)	0.620*** (0.017)	0.627*** (0.040)	0.521*** (0.015)	0.527*** (0.041)
[ln(material/labor)]²/2	0.130*** (0.009)	0.105*** (0.017)	0.075*** (0.014)	0.107*** (0.014)	0.121*** (0.011)	0.050** (0.019)
ln(capital/labor) *ln(material/labor)	-0.070*** (0.008)	-0.029 (0.024)	-0.039*** (0.015)	0.011 (0.025)	-0.041*** (0.014)	-0.017 (0.025)
I_m	0.112* (0.060)	0.147 (0.092)	0.247*** (0.074)	0.294*** (0.101)	0.269*** (0.074)	0.177* (0.089)
I_b	0.222 (0.270)	0.692*** (0.261)	-0.157 (0.182)	0.387*** (0.117)	0.269 (0.284)	0.476 (0.796)
I_{bm}	-0.197 (0.283)	-0.939*** (0.288)	-0.016 (0.316)	-0.498*** (0.148)	-0.692 (0.658)	-0.581*** (0.196)
I_m ln(R&D/labor)	0.013 (0.024)	0.051 (0.035)	0.037 (0.026)	0.110*** (0.036)	0.037* (0.021)	0.049 (0.031)
I_m ln(R&D/labor)²/2	0.024 (0.019)	-0.006 (0.018)	0.003 (0.018)	-0.008 (0.016)	-0.012 (0.014)	-0.005 (0.015)
I_b ln(TP/labor)	0.005 (0.058)	-0.080 (0.054)	0.069 (0.045)	0.004 (0.050)	0.057 (0.036)	0.100*** (0.032)
I_b ln(TP/labor)²/2	0.015 (0.063)	-0.036 (0.035)	0.039 (0.045)	-0.016 (0.029)	0.011 (0.021)	0.031** (0.014)
I_{bm} ln(R&D/labor) * ln(TP/labor)	0.014 (0.037)	0.073** (0.029)	0.002 (0.028)	0.013 (0.021)	0.006 (0.012)	0.005 (0.009)
SOE	-0.080 (0.058)	-0.137 (0.107)	-0.228*** (0.069)	-0.072 (0.106)	-0.362*** (0.049)	-0.336*** (0.075)
FOREIGN	0.221*** (0.070)	0.286*** (0.088)	0.221*** (0.064)	0.215*** (0.067)	0.132** (0.055)	0.171** (0.069)
EXPORT	0.019 (0.069)	0.007 (0.081)	0.111* (0.061)	0.076 (0.062)	0.202*** (0.053)	0.150** (0.062)
Constant	1.602*** (0.209)	1.576*** (0.395)	1.542*** (0.412)	1.152 (0.906)	2.278*** (0.418)	0.628 (0.967)
R-squared	0.775	-	0.707	-	0.744	-
Hansen overidentification test		chi2(56): 57.46		chi2(56): 56.34		chi2(56): 66.07
Prob > chi2		0.384		0.462		0.091
Difference-in-Hansen test		chi2(28): 32.02		chi2(28): 31.80		chi2(28): 24.10
Prob > chi2		0.231		0.283		0.625
Nb observations	1,304	1,304	1,026	1,026	1,002	1,002

*** p-value 0.01, ** p-value 0.05, * p-value 0.1. Industry and year dummies are included. When computing the marginal effects of I_b or I_m we take into account all the terms where these two dummies appear (i.e. five terms in total). For I_mln(R&D/labor) and I_bln(TP/labor), we include in the computation of the elasticities the effects of the square term and the interaction term. The marginal effects of I_mln(R&D/labor)²/2 and I_bln(TP/labor)²/2 represent second-order derivatives and the marginal effect of I_mln(R&D/labor)*I_bln(TP/labor) represents the second-order cross derivative of the unconditional expectation of new product sales/employee. For the marginal effects of ln(capital/labor) and ln(material/labor), square term and the interaction term are also accounted. Standard Errors are computed using the Delta Method. The marginal effects are evaluated at the means of the variables and only for positive values for R&D and TP.

3.6 Conclusion

This paper explores the impact of internal and external technology sourcing on firms' innovation and productivity performance in Chinese small- and medium-sized manufacturing firms. In particular, it investigates the returns of R&D and external technology purchasing (TP) and their possible complementarity or substitutability. It does so by distinguishing two performance measures: innovation in products or processes and labor productivity. Since size may matter in this regard, we estimate separately the relationships for firms with fewer than 100, between 100 and 300, and more than 300 employees.

Do Chinese firms need both R&D and TP in order to grow and catch up with technological frontier? Our evidence suggests (1) that firms with R&D are more innovative; (2) that firms with TP are (with the exception of process innovations in medium-sized firms) more innovative than non-TP firms; (3) that the elasticities or semi-elasticities of process or product innovation with respect to R&D and TP are positive whenever they are significant (with the exception of TP on product innovation intensity in small firms); (4) that the output elasticities of R&D and TP are always positive whenever they are significant and of a reasonable order of magnitude (around 0.10); and (5) that whenever there are significant estimates a complementarity exists between R&D and TP in promoting innovation or labor productivity.

External technology purchasing complements internal R&D in fostering innovation and labor productivity. To the extent that firms might not be sufficiently informed of this synergy in technology acquisition, it might be useful for the Chinese government to promote the adoption of both sources of technology acquisition. The somewhat surprising result is that firms that do both do not necessarily have the highest productivity performance. The exact reasons for this phenomenon, which could be duplication in knowledge acquisition, short-term adjustment costs, or other characteristics of those particular firms, would be worth exploring further.

Appendix 3A Calculating the marginal effects of explanatory variables on the unconditional expectation of new products sales per employee

The conditional expected value of y_2 is:

$$\begin{aligned} E(y_2|y_1^* > 0) &= \beta_2'X_2 + E(\varepsilon_2|\varepsilon_1 > -\beta_1'X_1) = \beta_2'X_2 + \varrho\sigma_2 \frac{\phi(\beta_1'X_1)}{\Phi(\beta_1'X_1)} \\ E(y_2|y_1 = 1) &= \beta_2'X_2 + E(\varepsilon_2|\varepsilon_1 > -\beta_1'X_1) = \beta_2'X_2 + \varrho\sigma_2 \frac{\phi(\beta_1'X_1)}{\Phi(\beta_1'X_1)} \end{aligned} \quad (3.a1)$$

$$\text{Using the inverse Mills Ratio } \lambda(a) = \frac{\phi(a)}{1-\Phi(a)} = \frac{\phi(-a)}{\Phi(-a)} = \frac{\phi(\beta_1'X_1)}{\Phi(\beta_1'X_1)} \quad (3.a2)$$

$$\text{where } a = \frac{-\beta_1'X_1 - E(\varepsilon_1)}{\sigma_1} = -\beta_1'X_1$$

ϕ and Φ are, respectively, the normal density function and the normal distribution function, y_2 represents new product sales per employee (innosale_{*i*}), X_i are the regressors of equation i where $i=1,2$ (index 1 refers to the selection equation (3.3.3) and index 2 to the intensity equation (3.3.2)), we can rewrite the conditional expected value of y_2 is:

$$E(y_2|y_1^* > 1) = \beta_2'X_2 + E(\varepsilon_2|\varepsilon_1 > -\beta_1'X_1) = \beta_2'X_2 + \varrho\sigma_2\lambda(a) \quad (3.a3)$$

The conditional marginal effects:

$$\frac{\partial E(y_2|y_1^* > 1)}{\partial x_i} = \beta_{2i} + \varrho\sigma_2 \frac{\partial}{\partial a} \left[\frac{\phi(a)}{1-\Phi(a)} \right] \frac{\partial(a)}{\partial x_i} = \beta_{2i} - \varrho\sigma_2\beta_{1i} \frac{\phi'(a)[1-\Phi(a)] + [\phi(a)]^2}{[1-\Phi(a)]^2} \quad (3.a4)$$

$$\phi'(a) = -(a) * \phi(a) \quad (3.a5)$$

$$\lambda(a)' = -\beta_{1j}\lambda(a)[\lambda(a) - a] \quad (3.a6)$$

$$\begin{aligned} \frac{\partial E(y_2|y_1^* > 0)}{\partial x_i} &= \beta_{2i} - \varrho\sigma_2(\beta_{1i}) \left\{ \frac{[\phi(a)]^2}{[1-\Phi(a)]^2} - \frac{(a) * \phi(a) * [1-\Phi(a)]}{[1-\Phi(a)]^2} \right\} \\ &= \beta_{2i} - \varrho\sigma_2(\beta_{1i}) \frac{\phi(-a)}{\Phi(-a)} \left[\frac{\phi(-a)}{\Phi(-a)} - a \right] \\ &= \beta_{2i} - \varrho\sigma_2\beta_{1i}\lambda(a)[\lambda(a) - a] \end{aligned} \quad (3.a7)$$

This is the marginal effect of x_i on the conditional expected value of y_2 . Here, we are considering only the effect of x_i on the value of y_2 for those having product innovation. Notice that the conditional marginal effect in (3.a7) depends on the vector X_1 , since $a = -\beta_1'X_1$. In general, the conditional marginal effect of a variable x_i will be different for each observation (individual). We shall evaluate it at the means of the observations for each variable.

The unconditional expected value of new product sales per employee is given by:

$$E(y_2|X) = E(\varepsilon_2|\varepsilon_1 > -\beta_1'X_1)\Phi(\beta_1'X_1) + E(\varepsilon_2|\varepsilon_1 < -\beta_1'X_1)\Phi(-\beta_1'X_1) \quad (3.a8)$$

Since $y_2 = 0$ if a firm has no product innovation: $\varepsilon_1 < -\beta_1'X_1$. Then (3.a8) can be

written as

$$E(y_2) = E(\varepsilon_2 | \varepsilon_1 > -\beta'_1 X_1) \Phi(\beta'_1 X_1) \quad (3.a9)$$

The unconditional effect is:

$$\begin{aligned} \frac{\partial E(y_2)}{\partial x_i} &= \Phi(\beta'_1 X_1) \frac{\partial (y_2 | y_1^* > 1)}{\partial x_i} + \beta_{1i} E(\varepsilon_2 | \varepsilon_1 > -\beta'_1 X_1) \Phi(\beta'_1 X_1) \\ &= \Phi(\beta'_1 X_1) \{ \beta_{2i} - \varrho \sigma_2 \beta_{1i} \lambda(a) [\lambda(a) - a] \} + \beta_{1i} [\beta'_2 X_2 + \varrho \sigma_2 \lambda(a)] \Phi(\beta'_1 X_1) \end{aligned} \quad (3.a10)$$

Following (3.a10), the second-order derivative with respect to x_j is:

$$\begin{aligned} \frac{\partial^2 E(y_2)}{\partial x_i \partial x_j} &= \Phi(\beta'_1 X_1) * \beta_{1j} * \{ \beta_{2i} - \varrho \sigma_2 \beta_{1i} \lambda(a) [\lambda(a) - a] \} - \Phi(\beta'_1 X_1) * \varrho \sigma_2 \beta_{1i} W \\ &\quad + \beta_{1i} \{ [\beta'_2 X_2 + \varrho \sigma_2 \lambda(a)] * [-\beta'_1 X_1 * \Phi(\beta'_1 X_1) * \beta_{1j}] + \Phi(\beta'_1 X_1) * Q \} \end{aligned} \quad (3.a11)$$

where

$$\begin{aligned} W &= [\lambda(a)^2 - \lambda(a) * a]' = 2\lambda(a) * \lambda(a)' - [\lambda(a)' * a + a' * \lambda(a)] \\ &= 2\lambda(a) * \{ \beta_{1j} \lambda(a) [a - \lambda(a)] \} - \{ \beta_{1j} \lambda(a) [a - \lambda(a)] * a - \beta_{1j} \lambda(a) \} \\ &= 2\beta_{1j} \lambda(a)^2 [a - \lambda(a)] - \beta_{1j} \lambda(a) \{ [a - \lambda(a)] * a - 1 \} \end{aligned} \quad (3.a12)$$

$$Q = [\beta'_2 X_2 + \varrho \sigma_2 \lambda(a)]' = \beta_{2j} + \varrho \sigma_2 \beta_{1j} \lambda(a) [a - \lambda(a)]. \quad (3.a13)$$

Chapter 4

Complementarity between internal knowledge creation and external knowledge sourcing in developing countries³⁶

4.1 Introduction

Much of the economic and social progress of the past few centuries has benefited from technological progress. Innovation has been considerably discussed in the endogenous growth theory (Aghion and Howitt, 1998; Grossman and Helpman, 1991), where it is modelled as being driven by an R&D sector. Although the number of studies examining the influence of innovation on productivity is increasing, most of the empirical studies on innovation and productivity have been conducted on developed country data (see Mairesse et al., 2011 for a review). In developing countries, innovation is more a process of learning and assimilation of knowledge in an effort to catch-up with the technological frontier than a process of creation and discovery (Fransman and King, 1984).

The current study will focus on knowledge sourcing strategies in developing countries. Two types of technology sourcing are distinguished. Firms can obtain new technologies by conducting their own R&D (MAKE) or they can acquire new technologies through licensing, hiring new personnel, or investing in new machinery (BUY). We shall address two questions: What are the comparative returns of the two sources of knowledge? And are the two substitutes or complements, i.e. is there a choice between one or the other, or should they be conducted jointly?

³⁶ This chapter leads to a joint working paper with Prof. P. Mohnen. UNU-MERIT WP 2013-10

The analysis is based on firm level data from 24 low- and middle-income countries³⁷. We test the existence of complementarity between MAKE and BUY by estimating demand equations for the two knowledge sourcing strategies, which are derived from a production function that allows for a synergy between them. This way of testing complementarity, which is borrowed from Miravete and Pernías (2006), allows the separate identification of a synergy between the two strategies and the unexplained correlation between the error terms in the respective demand equations. The result suggests that firms in low-income countries rely more on external sourcing and firms in middle-income countries more on in-house R&D, while a synergy between internal and external knowledge sourcing exists in middle-income countries but not in low-income countries.

This paper proceeds as follows. The next section sets the background by reviewing the feature of innovation strategies in developing countries and existing evidence on complementarity in innovation studies. Section 4.3 presents the empirical model and methods to estimate complementarity. The data and the variables used will be presented in section 4.4. The results are interpreted in section 4.5. The last section summarises and concludes.

4.2 MAKE and BUY in developing countries: complements or substitutes?

4.2.1 Something more than R&D?

Cooper (1989) explained the differences in characteristics between innovation in industrialized economies and developing countries. As he pointed out it is a rather limited view of innovation theories to be only concerned with the initial introduction of products or processes. Most firms in developing countries attempt to reach the technological frontier instead of achieving inventions that are new to the market.

At a low stage of development, firms normally face obstacles such as inadequate human capital and poor infrastructure. In-house innovative activities are severely constrained for a majority of firms. Freeman (1989) suggested that external knowledge sourcing has a significant influence on the learning process. He argued that for the most part even the most technologically advanced firms in developing countries are committed to be

³⁷ The classification into middle-income and low-income countries is taken from “World Bank country classification 2005”. See: <http://www.worldbank.org>

involved in external sourcing activities. Aggarwal (2000) explained that external technology plays two important roles in developing economies: filling gaps in domestic technological capability and upgrading the existing technologies to international standards. By enhancing the technological capability, external technology sourcing benefits in-house R&D.

However, acquiring external knowledge per se does not guarantee that a firm will achieve successful learning (Matusik, 2000). For external knowledge to be exploited effectively, it has to be combined with a complementary knowledge base within the firm. Cooper (1989) mentioned that failure to learn is in fact quite common in developing countries because the firms there that receive technology via external sources are quite often unconcerned about how to develop and appropriate this internal technological capability. Cohen and Levinthal (1989) define “absorptive capacity” to describe the substantial role of a stock of prior knowledge in order to absorb external know-how. They argue that the in-house R&D process would at the same time accommodate firms to build up their own technological capability. This technological capability within firms is needed in order to understand the tacit components of the technology (Desai, 1989; Lall, 1989; Mowey and Oxley, 1995).

The paradigm of open innovation demonstrates that firms should make the best use of internal and external knowledge (Chesbrough, 2003). This perspective not only emphasizes the significant value of external knowledge; it also indicates that firms organize their internal R&D in part in order to absorb the wealth of available external knowledge. Such a mutual interaction implies the possible complementary between own and external sources of knowledge.

4.2.2 Definition of complementarity

A pair of economic activities is complementary if (1) adopting one activity does not preclude adopting the other and if (2), whenever it is possible to implement each activity separately, the sum of the benefits of doing each separately is not greater than the benefit of doing both together (Milgrom and Robert; 1990a). The theorem states that if each pair of activities in a group is complementary, then implementing any subset of the activities in the group raises the incremental return to implementing the remaining ones (Topkis 1978). This notion of complementarity between activities was first introduced in

economics by Vives (1990) and then further developed by Milgrom and Roberts (1990b, 1995).

More formally, suppose there are two discrete technology acquisition practices, MAKE and BUY. Z is a vector of exogenous variables. The objective function $f(\text{MAKE}, \text{BUY}, Z)$ is supermodular if the following inequality holds for all values of the other arguments of f :

$$f(1, 1; Z) - f(1, 0; Z) > f(0, 1; Z) - f(0, 0; Z) \quad (4.1)$$

MAKE and BUY are complementary if the presence of one strategy (e.g. MAKE) increases the marginal return of adopting the other strategy (BUY), after controlling for other exogenous effects³⁸ (Milgrom and Robert, 1990b). Conversely, MAKE and BUY are substitutes if the inverse inequality holds for (4.1).

4.2.3 Evidence of complementarity in innovation studies

The notion of complementarity is commonly refer to cross-price effects in demand theory. During the past decades, many studies have broadened this concept to analyse more complex economic phenomena, organizational structures and government policies. Here, we briefly review some key studies in both economic and management literature that have estimated the complementarity versus substitutability in ways of technology sourcing.

In emerging economies, complementarity in innovation mainly focuses on investigating the inter-dependent relation between in-house R&D and imported technology. Braga and Willmore (1991) found that there is a robust complementary relationship between technology buying and firm technology effort in Brazilian industry. Deolalikar and Evenson (1989) showed that technology transferred from abroad and in-house R&D are complementary rather than substitutive avenues of technology acquisition. Kim and Nelson (2000) also argued that the process of learning through the external technology sourcing serves as an effective experience that paves the way for indigenous technological innovation in Indian firms.

³⁸ If MAKE and BUY are continuous variables, an equivalent inequality restriction would imply that the incremental effect of one practice on the objective function increases with an increase in the other practice:

$$\frac{\partial^2 f(r_b, r_m, Z)}{\partial r_b \partial r_m} > 0 \quad ; \text{ where } r_b \text{ is BUY and } r_m \text{ is MAKE.}$$

Besides, complementarity in innovation has also been shared by lots of studies across developed economies. Arora and Gambardella (1990) test the synergetic effects among four different external sourcing strategies of large American chemical and pharmaceutical firms. The results show that there is complementarity between all types of external sourcing strategies. Veugelers (1997) finds that the external sourcing strategy stimulates internal research activities in Belgian manufacturing firms. It seems that external knowledge sources leverage the innovative power of in-house R&D. This result is also found in a study undertaken by Lokshin, Belderbos and Carree (2008). In a recent study Cassiman and Veugelers (2006) found a strong synergy relationship between firms' internal R&D and disembodied knowledge sourcing strategies in Belgian manufacturing firms.

On the other hand, some studies have found evidence on substitutability between innovation activities. Mytelka (1987) found that external imports of technology discourage Andean group countries to undertake in-house innovation activities. Fikkert (1993) used the Indian manufacturing firm data to regress the technology imports on in-house R&D efforts. Their findings support the hypothesis of negative relationship between technology imports and R&D efforts. Basant and Fikkert (1996) estimated the return of R&D, technology imports and their interaction term in the production function by using Indian firm level panel data. They found that the estimated rate of return of technology imports is much higher than the return to in-house R&D. The results also imply a substitutive relation between R&D efforts and external technology in the production of knowledge. Katrak (1997) also found that the probability of importing technology was only weakly influenced by R&D efforts and the external sourcing had a significant negative effect on the R&D labor intensity in Indian electrical and electronics industries.

Despite the rich literature on technology making and buying in developing countries, the results are far from conclusive. What distinguishes this study from the previous studies is, first of all, the use of a recent methodology for testing complementarity that controls for the correlation between unobservables in the strategy equations, and, secondly, the use of a unique dataset of 24 developing countries that allows to investigate differences in complementarity at different levels of development.

4.3 Testing for complementarity

In this section we explain the way complementarity in technology acquisition strategies can be identified and tested.

In empirical studies, the most popular approach applied to investigate complementarity between economic activities consists in directly estimating the cross partial derivatives in the production function. This approach is defined as the Production approach (PROD). It aims at testing the complementarity for a specific objective function. It has been applied in several empirical studies (Cassiman and Veugelers, 2006; Mohnen and Röller, 2005; Belderbos et al., 2006).

Suppose that firm i uses two knowledge acquisition strategies, y_{mi} referring to MAKE or internal knowledge acquisition, and y_{bi} , referring to BUY or external knowledge acquisition. The technology is represented by a standard Cobb-Douglas production function $Q_i = f(K_i, L_i, y_{mi}, y_{bi}, Z_i)$, where K and L represent respectively capital and labor, and Z stands for a group of control variables that capture the firm- and organization-specific characteristics. In logarithmic terms, denoting logarithmically transformed continuous variables by small letters, we have

$$q = \alpha k_i + \beta l_i + \theta_{00}(1 - y_{bi})(1 - y_{mi}) + \theta_{10}y_{bi}(1 - y_{mi}) + \theta_{01}(1 - y_{bi})y_{mi} + \theta_{11}y_{bi}y_{mi} + \chi Z_i + e_i \quad (4.2)$$

where α and β are the output elasticities of capital and labor, y_{ji} ($j=b,m$) are binary choice variables taking the value 1 if the corresponding strategies are adopted by firm i , θ_{11} , θ_{01} , θ_{10} , and θ_{00} captures the productivity obtained when respectively MAKE and BUY, only BUY, only MAKE and neither MAKE nor BUY are chosen, and e_{it} is a random error term.

The PROD approach estimates the existence of complementarity directly by regressing the objective function on exclusive combinations of innovation activities. The production function is supermodular in y_{bi} and y_{mi} if

$$\theta_{11} - \theta_{01} - \theta_{10} + \theta_{00} > 0 \quad (4.3)$$

The inequality expresses the fact that the presence of one innovation activity increases the marginal return of adopting another activity. Conversely, the two activities are substitutive if

$$\theta_{11} - \theta_{01} - \theta_{10} + \theta_{00} < 0 \quad (4.4)$$

An alternative form can be written in the follow way:

$$q = \alpha k_i + \beta l_i + \theta_0 + \theta_b y_{bi} + \theta_m y_{mi} + \theta_{bm} y_{bi} y_{mi} + \chi Z_i + e_i \quad (4.5)$$

where

$$\begin{aligned} \theta_0 &= \theta_{00} \\ \theta_b &= \theta_{10} - \theta_{00} \\ \theta_m &= \theta_{01} - \theta_{00} \\ \theta_{bm} &= \theta_{11} + \theta_{00} - \theta_{10} - \theta_{01}. \end{aligned} \quad (4.6)$$

Coefficient θ_m captures the non-exclusive partial effects of MAKE, θ_b the non-exclusive partial effect of BUY, θ_{bm} the returns of adopting MAKE and BUY together; θ_0 is constant. The condition for supermodularity now simplifies to:

$$\theta_{bm} = \theta_{11} + \theta_{00} - \theta_{10} - \theta_{01} > 0 \quad (4.7)$$

It is worth noting under (4.5) the marginal returns to either MAKE or BUY will not be constant anymore if complementarity or substitutability is observed ($\theta_{bm} \neq 0$). Henceforth, the marginal returns of MAKE and BUY should be expressed respectively as

$$\begin{aligned} [f | y_m = 1] - [f | y_m = 0] &= \theta_m + \theta_{bm} y_b \\ [f | y_b = 1] - [f | y_b = 0] &= \theta_b + \theta_{bm} y_m \end{aligned}$$

Athey and Stern (1998) explain that simply running OLS on the above function would deliver inconsistent results. They argue that the existence of firms' unobserved heterogeneity correlated with the strategy decisions may make the PROD approach fail to generate consistent estimators.

In order to correct for this bias, one should either use instrument variables with cross sectional data or control for the unobserved heterogeneity if panel data are available (Wooldridge, 2002). Cassiman and Veugelers (2006) have tried to adopt instrumental variables that were correlated with the adoption decisions without affecting innovation output. However, the results can be refined only if the instrumental variables are properly identified. In the current case, neither the input price (especially for BUY) that

each firm faces in adopting innovation practices nor factors that affect the return to those practices are observed by the econometrician.

In the following part, we introduce another approach of testing for complementarity, which was originally developed by Miravete and Pernías (2006 and 2010) and later extended in Kretschmer, Miravete and Pernías (2012). This approach tests for “behavioral complementarity” and can be classified somewhere between the PROD approach introduced above and what is known in the literature as the CORR approach. The latter tests whether there remains a correlation between the error terms of the reduced forms of two strategy equations, which are derived without necessarily specifying any objective function. In contrast, in the Miravete and Pernías (MP) approach we specify an objective function, although in the end the estimation is based on the parameterization of the individual returns of each strategy³⁹. Compared with the PROD approach we model explicitly the endogeneity of the strategy choices⁴⁰. Table below compares three approaches. Apart from not specifying an objective function, the CORR approach imposes two assumptions: firms are assumed to make rational choices and there are no correlations between the unobserved factors that affect the activities concerned. The MP approach differs from the CORR approach by releasing the second assumption.

Different approaches to test complementarity in cross sectional analysis

Approach	Category	Objective function	Assumptions
PROD	Objective	Yes	No unobservables
CORR	Behavior	No	Optimal choices & No unobservables
MP (Miravete and Pernías)	Objective/Behavior	Yes	Optimal choices

Here, we start from the production function (4.8) by introducing both observed and unobserved factors, W_{ji} and ε_{ji} respectively, which are both interacted with input

³⁹ In Kretschmer, Miravete and Pernías (2012) the objective function is estimated together with the strategy choice equations.

⁴⁰ The simple version is using the Pearson correlation or conditional correlation between the residuals to test for the association between two or more activities. A number of empirical studies use this approach as auxiliary evidence. For example: Arora and Gambardella (1990) introduce a formal analysis of CORR as a test for complementarity. Brickley (1995) explicitly uses CORR as a test for the comparative static predictions of Holmström and Milgrom (1994) in the context of franchising contract provisions. A critical assumption underlying this approach is the absence of covariance between the residuals of the strategy equations conditional on the characteristics of the firm.

strategies MAKE and BUY in determining the productivity performance. The W_{ji} ($j=b,m$) are observed factors, which capture things like the firms' past innovation experience and its absorptive capacity that can influence the return from the corresponding innovation strategy. Control variables are defined differently in determining the return of MAKE and BUY in order to avoid the identification problem. The ε_{ji} 's ($j=b,m$) capture unobserved factors that can influence the choice of MAKE and/or BUY, such as the appropriation regime or management practices, and factors that cannot be quantitatively or qualitatively identified. The production function is now given as

$$q_i = \alpha k_i + \beta l_i + (\theta_b W_{bi} + \delta_{bm} y_{mi} + \varepsilon_{bi}) y_{bi} + (\theta_m W_{mi} + \delta_{bm} y_{bi} + \varepsilon_{mi}) y_{mi} + \chi Z_i + e_i \quad (4.8)$$

Let

$$\lambda_{bi} = \theta_b W_{bi}; \lambda_{mi} = \theta_m W_{mi} \quad (4.9)$$

On the right-hand side of equation (4.8), $(\lambda_{bi} + \delta_{bm} y_{mi} + \varepsilon_{bi})$ and $(\lambda_{mi} + \delta_{bm} y_{bi} + \varepsilon_{mi})$ measure respectively the percentage differences in productivity level when choosing 1 instead of 0 for each of the two strategies, holding the other one fixed. Specification (4.8) is borrowed from Lewbel (2007). He shows that a specification like (4.8) eliminates the incoherency and incompleteness problems in simultaneous equations with binary variables, by specifying as an objective function that incorporates the individual returns derived from each individual strategy. Equation (4.8) differs from the PROD approach in that it captures not only the possible interaction between the input strategy variables and the technological capability λ_{ji} , but also the potential endogeneity of the strategy choices by including ε_{ji} , which is possibly correlated with y_{ji} . The existence of complementarity can only be concluded when controlling for both observed and unobserved characteristics.

We shall estimate equation (4.8) by maximum likelihood. Before we derive the likelihood function, two important assumptions need to be made. Because of the absence of information regarding the cost associated to the two innovation strategies, we are not able to derive a cost function, hence we assume that firms behave optimally by maximizing their productivity. Second, in order to avoid an identification problem, we

assume that the unobserved error terms $(\varepsilon_{bi}, \varepsilon_{mi})$ follow a standard bivariate normal distribution with a correlation coefficient ρ_{bm} .

The firm has to decide on whether to adopt or not each of the two innovation strategies (MAKE and/or BUY). Therefore, four choice combinations are possible: D(1,1), D(1,0), D(0,1), D(0,0). The firm will choose the combination that yields the highest productivity. For each of the four possible choices we will get a corresponding set of inequality restrictions as follows⁴¹:

$$\begin{aligned}
 D_{(1,1)} &\Rightarrow \left\{ \begin{array}{l} f(1,1) > f(0,1) \\ f(1,1) > f(1,0) \\ f(1,1) > f(0,0) \end{array} \right\} = \left\{ \begin{array}{l} \varepsilon_{bi} > -\lambda_{bi} - 2\delta_{bm} \\ \varepsilon_{mi} > -\lambda_{mi} - 2\delta_{bm} \\ \varepsilon_{mi} > -\lambda_{bi} - \lambda_{mi} - 2\delta_{bm} - \varepsilon_{bi}^* \end{array} \right\} \\
 D_{(1,0)} &\Rightarrow \left\{ \begin{array}{l} f(1,0) > f(1,1) \\ f(1,0) > f(0,1) \\ f(1,0) > f(0,0) \end{array} \right\} = \left\{ \begin{array}{l} \varepsilon_{mi} < -\lambda_{mi} - 2\delta_{bm} \\ \varepsilon_{mi} < \lambda_{bi} - \lambda_{mi} + \varepsilon_{bi}^* \\ \varepsilon_{bi} > -\lambda_{bi} \end{array} \right\} \\
 D_{(0,1)} &\Rightarrow \left\{ \begin{array}{l} f(0,1) > f(1,1) \\ f(0,1) > f(1,0) \\ f(0,1) > f(0,0) \end{array} \right\} = \left\{ \begin{array}{l} \varepsilon_{bi} < -\lambda_{bi} - 2\delta_{bm} \\ \varepsilon_{mi} > \lambda_{bi} - \lambda_{mi} + \varepsilon_{bi}^* \\ \varepsilon_{mi} > -\lambda_{mi} \end{array} \right\} \\
 D_{(0,0)} &\Rightarrow \left\{ \begin{array}{l} f(0,0) > f(1,1) \\ f(0,0) > f(1,0) \\ f(0,0) > f(0,1) \end{array} \right\} = \left\{ \begin{array}{l} \varepsilon_{mi} < -\lambda_{bi} - \lambda_{mi} - 2\delta_{bm} - \varepsilon_{bi}^* \\ \varepsilon_{bi} < -\lambda_{bi} \\ \varepsilon_{mi} < -\lambda_{mi} \end{array} \right\}
 \end{aligned} \tag{4.10}$$

If D(1,1) is the optimal choice, the first set of inequality restrictions in (4.10) automatically satisfy the supermodular condition (4.1). This can be proved by:

First, adding the first two inequality for D(1,1) in (4.10), we will have

$$\varepsilon_{bi} + \varepsilon_{mi} + \lambda_{bi} + \lambda_{mi} + 4\delta_{bm} > 0; \tag{4.11}$$

then rearranging the third inequality of D(1,1) and putting the left sequence to the right,

$$\varepsilon_{bi} + \varepsilon_{mi} + \lambda_{bi} + \lambda_{mi} + 2\delta_{bm} > 0; \tag{4.12}$$

⁴¹ $f(y_{bi}, y_{mi})$ is derived from equation (8). Here, the form of D(1,1) is the sum of returns in choosing both MAKE and BUY: $(\lambda_{bi} + \delta_{bm}y_{mi} + \varepsilon_{bi}) + (\lambda_{mi} + \delta_{bm}y_{bi} + \varepsilon_{mi})$. This specific form for D(1,1) enables us to avoid the incoherency and incompleteness problems (Lewbel, 2007).

finally, subtracting (4.12) from (4.11), we obtain the supermodularity condition

$$D(1,1) - D(1,0) > D(0,1) - D(0,0) \\ \Rightarrow (\lambda_{bi} + \delta_{bm} + \varepsilon_{bi}) + (\lambda_{mi} + \delta_{bm} + \varepsilon_{mi}) - (\lambda_{bi} + \varepsilon_{bi}) > (\lambda_{mi} + \varepsilon_{mi}) - 0 \Rightarrow 2\delta_{bm} > 0. \quad (4.13)$$

In the structural form, firms need to reach decisions by considering both the expected returns of doing MAKE/BUY and their possible synergy. If there is a synergistic effect, firms will engage in both activities together and we expect to see the existence of complementarity, which will be exhibited as $2\delta_{bm} > 0$. What is important to notice is that the estimation will control for the presence of the correlation between error terms, ρ_{bm} , which may cause the two strategies to be adopted jointly but for other reasons than complementarity between them.

In order to write the likelihood function, there are three situations that should be considered separately. First, if $\delta_{bm} = 0$, which implies that there is no complementarity MAKE and BUY, (4.10) will be transformed into a likelihood function that corresponds to the standard bivariate probit model. There is no interaction between the returns of individual strategies, and hence each strategy is separately chosen depending on whether its return is above a certain threshold. Second, if $\delta_{bm} > 0$, the inequalities for $D(1,1)$ and $D(0,0)$ in (4.10) that are marked with an asterisk are binding. Last, if $\delta_{bm} < 0$, it is the inequalities marked with an asterisk for $D(1,0)$ and $D(0,1)$ in (4.10) that are binding. Figure 4.1 adapted from Miravete and Pernias (2006), which represents the regions of strategy choices in the space of $(\varepsilon_b, \varepsilon_m)$ gives us a clear picture of the difference between the regions of strategy choices in the bivariate probit model and in the presence of complementarity (or substitutability). If $\delta_{bm}=0$, the regions corresponding to the strategy profiles are in a rectangular fashion orthogonal to each other. If $\delta_{bm} > 0$, the regions contours will no longer be rectangular as in the bivariate probit model. Even for some values below the individual thresholds pertinent to the adoption of individual strategies, the two strategies (MAKE and BUY) can be adopted jointly because of their complementarity. Conversely, if $\delta_{bm} < 0$, the space for individual (non-joint) strategy adoption is much larger than when $\delta_{bm} > 0$ because strategies are substitutes for each other.

Figure 4.1 Regions corresponding to strategy choices in the $(\varepsilon_b, \varepsilon_m)$ space

The likelihood function will reproduce the probability of observing pairs of strategies that are determined by the inequality constraints in (4.10).

$$\begin{aligned}
 & L_i(\alpha, \beta, \chi, \theta_b, \theta_m, \delta_{bm}, \rho_{bm}; y_{bi}, y_{mi}, Z_i) \\
 &= \sum_{i=1}^n \left\{ y_{bi} y_{mi} \ln P_{(1,1)} + y_{bi} (1 - y_{mi}) \ln P_{(1,0)} + (1 - y_{bi}) y_{mi} \ln P_{(0,1)} + (1 - y_{bi})(1 - y_{mi}) \ln P_{(0,0)} \right\} \quad (4.14)
 \end{aligned}$$

where

$$\begin{aligned}
 P_{(1,1)} &= \int_{-\lambda_{bi}-2\delta_{bm}}^{\infty} \int_{\max[(-\lambda_{mi}-2\delta_{bm}), (-\lambda_{bi}-\lambda_{mi}-2\delta_{bm}-\varepsilon_{bi})]}^{\infty} \phi_2(\varepsilon_{bi}, \varepsilon_{mi}, \rho_{bm}) d\varepsilon_{bi} d\varepsilon_{mi} \\
 P_{(1,0)} &= \int_{-\lambda_{bi}}^{\infty} \int_{\min[(-\lambda_{mi}-2\delta_{bm}), (\lambda_{bi}-\lambda_{mi}+\varepsilon_{bi})]}^{\infty} \phi_2(\varepsilon_{bi}, \varepsilon_{mi}, \rho_{bm}) d\varepsilon_{bi} d\varepsilon_{mi} \\
 P_{(0,1)} &= \int_{-\lambda_{bi}-2\delta_{bm}}^{\infty} \int_{\max[(-\lambda_{mi}), (\lambda_{bi}-\lambda_{mi}+\varepsilon_{bi})]}^{\infty} \phi_2(\varepsilon_{bi}, \varepsilon_{mi}, \rho_{bm}) d\varepsilon_{bi} d\varepsilon_{mi} \\
 P_{(0,0)} &= \int_{-\infty}^{\infty} \int_{-\lambda_{bi} \min[(-\lambda_{bi}), (-\lambda_{bi}-\lambda_{mi}+2\delta_{bm}-\varepsilon_{bi})]}^{\infty} \phi_2(\varepsilon_{bi}, \varepsilon_{mi}, \rho_{bm}) d\varepsilon_{bi} d\varepsilon_{mi}
 \end{aligned}$$

where $P_{(1,1)}$, for instance, denotes the probability of observing the strategy pair (1,1). The same goes for the other pairs. In addition to the parameters in the production function (4.8), the correlation coefficient ρ_{bm} will also be estimated. The estimation of a truncated bivariate probit with upper and lower bounds is achieved by adopting the maximum simulated likelihood estimator using the GHK simulator (Hajivassiliou and Ruud, 1994; Greene, 2003)⁴².

4.4 Data and variables

4.4.1 Data

The data that we use in our empirical analysis come from the World Bank Investment Climate Surveys (ICS)⁴³. These surveys have been conducted mostly in developing countries and provide us a wide range of information about innovative performance, economic activities and the investment environment of firms. Several aspects referring to

⁴² The estimation of likelihood function (4.14) is conducted by using statistical program STATA 10.2. The corresponding programming code is available upon request.

⁴³ For more information and the methodology of the survey, please see <http://www.worldbank.org>

firms' innovation behavior are covered in the survey, in particular firms' R&D input, licensing and other external sourcing channels.

After removing missing values and cleaning for outliers, we are left with 9,086 firms across 24 countries in the manufacturing sector in the pooled cross-sectional dataset from the period 2002-2005⁴⁴. Due to differences in the size of the economies and the survey methods adopted across countries and regions, the number of firms in the samples varies considerably across countries. Only countries with more than 50 observations are included⁴⁵. Table 4.1 presents descriptive statistics about the countries and their innovativeness. Innovativeness here means having introduced a product or a process innovation.

As shown in Table 4.1, innovation is rather pervasive across countries with approximately 58 per cent of them claiming to have been innovative during the period under review. It should be noted again that these numbers do not represent inventions nor introductions of products or processes new to the market. They are more likely to be innovations new to the firm, sometimes considered as imitative innovations. Among all countries in our sample, Brazil is the most innovative country with 86 per cent of firms having had product or process innovations in the period under survey. In second place comes South Africa with 82 per cent. Ethiopia and Pakistan have no information with respect to innovation output⁴⁶.

The survey contains two main questions regarding firms' knowledge acquisition strategies. First, firms were asked to choose the three most important methods of knowledge sourcing out of a total of twelve options. The dummy variable BUY gets value 1 if firms chose at least one of the following three technological sources: importing machinery and equipment, hiring key personnel or licensing from abroad or domestically. Second, the survey has questions related to firms' R&D spending in the last year of the

⁴⁴ We did not use the standardized dataset provided by the World Bank due to inconsistencies in the questionnaires and measurements (e.g. currencies). Instead, we cleaned the data country by country because the standardized dataset does not always cover all the information provided by firms. Additionally, the currency unit in the standardized data also caused some confusion, which needed to be traced back to each country's questionnaire. Furthermore, the service sector is not included because the innovation inputs (R&D and external sourcing) are not reported. Furthermore, following Hall and Mairesse (1995), we only keep observations for which the capital-labor ratio was within three times the inter-quartile range (the difference between the 75% value and the 25% value) above or below the median, which is about 6 percentage of total sample.

⁴⁵ A sample with fewer than 50 observations is unlikely to give us consistent estimates of the country specific effect. We also dropped firms with fewer than 5 permanent employees and growth of sales per person above 300 per cent. In total we eliminated in this way about 3% of all the observations.

⁴⁶ This is not problematic to our further analysis since our main concern is the productivity performance.

survey period. R&D expenditures cover all outlays (labor costs, materials, expenditures on tangible fixed assets) incurred for research activities that comprise “creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications” (OECD, 2011). The dichotomous variable MAKE takes value 1 if firms claim to have positive R&D spending during the period of the survey, 0 otherwise.

Table 4. 1 Innovativeness of firms in developing countries

Country	Year	Observation (firms)	Income ⁴⁷	Percentage of innovators	Output per worker (log, 1000 USD/person)	Capital per worker (log, 1000 USD/person)	Labor (log, person)
Brazil	2003	1463	Lower-Middle income	85.99%	2.58	2.03	4.00
Chile	2004	306	Higher-Middle income	51.31%	3.70	3.69	3.90
Costa Rica	2005	88	Higher-Middle income	78.41%	3.01	2.74	3.47
Ecuador	2003	273	Lower-Middle income	75.46%	2.92	2.71	3.67
Egypt	2004	582	Lower-Middle income	11.51%	1.47	1.46	3.37
El Salvador	2003	280	Lower-Middle income	80.71%	2.69	2.60	3.79
Ethiopia	2002	243	Low income	missing	1.51	2.16	3.64
Guatemala	2003	371	Lower-Middle income	72.78%	2.41	2.19	3.58
Guyana	2004	97	Lower-Middle income	54.64%	2.52	2.73	3.09
Honduras	2003	323	Lower-Middle income	66.25%	2.19	1.98	3.28
Indonesia	2003	466	Lower-Middle income	46.35%	1.86	1.76	5.23
Lithuania	2004	74	Higher-Middle income	39.19%	2.18	0.94	3.79
Madagascar	2005	79	Low income	60.76%	1.50	1.65	4.11
Malawi	2005	84	Low income	64.29%	2.34	2.03	4.15
Mauritius	2005	98	Higher-Middle income	72.45%	2.70	2.40	4.12
Nicaragua	2003	308	Low income	75.00%	1.77	1.73	2.95
Pakistan	2002	845	Low income	missing	2.31	2.29	3.30
Philippines	2003	582	Lower-Middle income	59.79%	1.97	1.57	4.16
South Africa	2003	513	Lower-Middle income	82.85%	3.47	2.85	4.69
Syria	2003	75	Lower-Middle income	36.00%	1.83	2.70	2.23
Tanzania	2003	73	Low income	49.32%	2.09	2.21	3.51
Thailand	2004	1336	Lower-Middle income	64.97%	2.85	2.49	4.96
Turkey	2005	454	Higher-Middle income	69.16%	3.54	3.32	4.20
Zambia	2002	73	Low income	72.60%	2.54	2.24	4.07
Total		9086		57.67%	2.50	2.26	4.02

Table 4.2 shows the count statistics of the appearance of each strategy and their interactions. We do not distinguish between higher- and lower-middle income countries,

⁴⁷ Countries are divided according to 2011 GNI per capita, calculated using the World Bank Atlas method (<http://data.worldbank.org/about/country-classifications/world-bank-atlas-method>). Low-income countries: 1,025 USD or less; lower middle-income countries: 1,026 - 4,035 USD; upper middle-income countries: 4,036 - 12,475 USD; and high-income countries: 12,476 USD or more. We have aggregated low-middle and higher-middle into one group: middle-income countries.

only between the union of those two and low-income countries. The statistics show that the main technology sourcing in low- and middle-income countries is external. Given the low levels of financial and human resources, firms seek innovation sources from external channels. There is about a 9 per cent higher frequency in pursuing the non-exclusive BUY strategy and a slightly lower probability of adopting the non-exclusive MAKE strategy in middle-income compared with low-income countries. Turning to the exclusive strategies (columns 3 to 6), we see that firms are more likely to adopt MAKE and BUY in middle-income than in low-income countries, 21.8 per cent versus 17.5 per cent. At a relatively higher level of development firms have probably accumulated some knowledge stocks and have gained experience that make them capable of doing in-house R&D and external BUY simultaneously. One should note that there are also other existing knowledge sourcing strategies, such as knowledge transfer from mother companies, learning from international conferences or study trips. We will not address these strategies here.

Table 4. 2 "Make" and "Buy" strategies in low- and middle-income countries

Income level	MAKE	BUY	MAKE ONLY	BUY ONLY	MAKE AND BUY	NO MAKE OR BUY	Innovation
Low-income countries	31.09%	56.54%	13.55%	39.00%	17.54%	29.91%	24.75%
Middle-income countries	28.84%	67.05%	7.02%	45.22%	21.83%	25.93%	65.28%
Total	29.26%	65.08%	8.24%	44.06%	21.02%	26.68%	57.67%

4.4.2 Specification of the production function

Table 4.3 provides the definition for each variable used in our empirical analysis. Two sets of variables will be introduced in accordance with the two methods adopted in the empirical analysis, one for the PROD approach and the other one is for the MP approach. The dependent variable in the PROD approach is productivity, measured by sales per employee, in natural logarithmic terms. The standard explanatory variables in the production function (4.5) are: physical capital (total end-of-year capital per person in logs), labor (log of permanent workers at the end of the year). Sales and capital are converted in 1000 USD. Besides the standard explanatory variables, we also control for differences in capacity utilization (in percentage) because firms are likely to be more

productive with the same amount of inputs when they operate at a relatively high level of capacity utilization.

Variable EXPORT indicates whether firms had positive export sales during the last year. Here, we use EXPORT to indicate the level of openness of the economy. Openness has generally led to greater competition in the product markets and increasingly also in the market for services. More vigorous competition exerts discipline on firms in developing countries. It therefore tends to strengthen incentives for development in their economy. So we expect a positive relation between export activities and firm performance.

The ICS survey contains a series of information about the business environment in which firms operate. The business environment consists of government regulations, institutional background, or social conventions, which are believed to have a substantial impact on firms' production decisions and performance (Coase, 1998). Questions are asked about obstacles to innovation on a four-point Likert scale. We select the infrastructure, regulation, and financial innovation hindrances and transform these variables in binary variables. The dummy variables Infra_obs, Regu_obs and Finance_obs take value 1 if the answer is marked as a major or very severe obstacle (scores 3 and 4). It is believed that these economic and institutional obstacles can play a significant role in explaining the heterogeneous performance in productivity across countries (Mohnen and Röller, 2005). Size⁴⁸, industry and country dummies⁴⁹ are used to capture the heterogeneities due to size, industries and countries.

4.4.3 Specification of the knowledge acquisition equations

Two categories of variables are expected to affect firms' knowledge sourcing strategies. The first category is firm specific. It includes size and foreign ownership (Foreign-owner). Larger firms are expected to be more innovative and hence have more often internal R&D activities and external technology purchases. Most of the foreign firms in developing countries are more competitive than the domestic firms. However, empirical evidence has shown that in joint ventures the core technologies remain generally under the control of the foreign partners or of company headquarters abroad (OECD, 2007). So, in general, foreign-owned companies are expected to be less likely to engage in innovation activities than domestic firms.

⁴⁸ Small firms: < 20 employees; medium size firms: 21-99 employees, large size firms > 100 employees.

⁴⁹ Four regions are included: European, African, Asian and Latin American countries.

Table 4. 3 Definition of variables

Dependent variable		PROD	MP
PRODUCTIVITY	Total sales /Number of long-term permanent workers, in 1000USD, in logs	√	
Explanatory Variables			
Capital	Total assets of firms (including Property, Plant and Equipment)/Number of long-term permanent workers, in 1000 USD and in logs	√	
Labor	Number of long-term permanent workers	√	
Capacity	Actual output produced (1000 USD)/ Maximum output that could be produced with existing machinery and equipment and regular shifts (value between 0-1)	√	
Innovation strategy variable			
MAKE	Dummy variable equal to 1 if firms have own R&D activities and have a positive R&D budget	√	√
BUY	Dummy variable equal to 1 if firms acquire technology through at least one of the following external technology acquisition methods: importing machinery and equipment; hiring key personnel; licensing	√	√
Control variables			
Foreign_owner	Dummy variable equal to 1 if a firm has foreign ownership		√
Exporter	Dummy variable equal to 1 if firm's sales are exported		√
Edu_manager	Dummy variable equal to 1 if manager have graduate school or above education		√
Training	Dummy variable equal to 1 if training took place		√
IT	Dummy variable equal to 1 if firms use internet or have own website		√
ISO	Dummy variable equal to 1 if a firm has ISO (international certification)		√
Co-supply/customer	Dummy variable equal to 1 if a firm has co-operative innovation activities with suppliers or customers		√
Co_university	Dummy variable equal to 1 if a firm has co-operative innovation activities with universities		√
Finance_obs	Dummy variable with the value 1 if accessing to finance or costs of finance is a major obstacle to firm	√	
Infra_obs	Lost value of sales due to power outages during last operation year, in percentage	√	
Regu_obs	The average time of managers dealing with government regulations	√	
Industry dummy	Definition of industrial categories and Low-tech industries from OECD ⁵⁰	√	√
Country dummy	Countries included in our study	√	

⁵⁰ See <http://www.oecd.org>

The second category of variables is intended to capture the technological capability that affects firms' innovation strategy decisions. Because information technology is commonly recognized as an important technological infrastructure to improve communication and logistics efficiency, IT is included in both the returns of MAKE and BUY. Dummy variable ISO with value 1 indicates that the firm has received international certificates, for example ISO9000, ISO9002 or ISO14000. ISO standards in general represent a reservoir of technology. In developing countries, ISO standards are an important means both of acquiring technological know-how and of raising the capability to compete in global markets. ISO certifications to some extent reflect the technological capability and experience of firms. Training will be included only in the MAKE function. It gets value 1 if firms carry out a training program for their employees. Skilled labor is an essential part of firms' innovation capacity to accommodate and integrate the new knowledge into production and ultimately transform it into new products or processes. Dummy variable Edu_manager has a value 1 if the average education level of senior managers is above the university level. It will only be included in the BUY equation.

Dummy variable Co_supply/customer indicates collaboration with suppliers and customers, which is believed to be associated with input quality improvements aimed at cost reductions or market expansion (Von Hippel, 1988; Tether, 2002). Co_university indicates if firms cooperate with universities and research institutes. It is generally associated with radical, breakthrough innovations that may open up entire new markets or market segments (Tether, 2002; Monjon and Waelbroeck, 2003). These two indicators are also widely used to measure a firm's absorptive capacity (Zahra and George, 2002; Schmidt, 2005; Freel and Harrison, 2006).

Figure 4.1 depicts the differences in the mean values of the explanatory variables between low-income and middle income countries. Clearly, technological capability and institutional environment are heterogeneous across levels of development. The pattern exhibits that the mean values of technology-related variables is generally higher in middle-income than in the low-income countries. One exception in our sample is the managers' education that is higher in the low-income group, which might be due to the differences in the education across different countries.

It is worth highlighting the pattern of technological capability across different income groups here. Lane and Lubatkin (1998) suggest that firms learn from firms that have

similar characteristics. Dussauge et al. (2000) and Cohen and Levinthal (1990) use the path-dependency theory to conclude that a firm is better able to acquire and use knowledge sourcing if it has some prior experience or higher technological capability. With low levels of development firms might be constrained by generally low levels of technological capability. Hence, firms in low-income countries might rely mainly on external technology acquisitions. Additionally, the synergy effect of MAKE_and_BUY on productivity performance will be undermined by factors such as weak infrastructure, scarce financial resources, etc. The increase of technological capability will catalyze the speed and efficiency of absorbing external know-how; hence we argue that the complementarity between in-house and external knowledge sourcing strategies is expected to appear as the level of development increases. The last three columns in figure 4.2 show the mean values of the infrastructure, financial and regulation obstacles that firms face. At least the infrastructure and finance related obstacles are more severely felt in low-income countries.

Figure 4.2 Innovation sourcing strategies, firm specificities and institutional characteristics in low-income and middle-income countries

4.5. Empirical results

This section discusses the result of empirical analysis on the role of technology-sourcing strategies in affecting firms' performance. In particular, we would like to see whether there are synergy effects between them. As shown in Table 4.4, a simple correlation between MAKE and BUY regardless of any other differences in firms' characteristics gives a Pearson coefficient of -0.0017 (non-significant at 10 per cent) for the low-income countries and 0.1167 (significant at 1 per cent) for the middle-income countries. This finding suggests an association between innovation sourcing strategies in middle-income countries. However, as stated before, the correlation observed here may be caused by firm specificities. It is unwarranted to draw a conclusion at this stage.

Table 4. 4 Unconditional correlations between innovation strategies and scale of investment

	Low-income countries		Middle-income countries	
	MAKE	BUY	MAKE	BUY
MAKE	1		1	
BUY	-0.0017	1	0.1167***	1

***indicates the results is significant at 0.01.

4.5.1 PROD approach

Based on equation 4.5, we regress firms' productivity (in logarithm) on the innovation strategies MAKE and BUY while controlling for other firm, industry and country specificities, which may affect the productivity performance. The results are given in Table 4.5.

We separate the sample into two groups according to their income levels. The first two columns of Table 4.5 are the results without interaction term between MAKE and BUY while the last two columns include it. Except for the technological sourcing variables, the estimated coefficients of the other variables do not differ considerably when controlling or not for the interaction term.

As shown in Table 4.5, different patterns are observed across different income levels with respect to the determinants of productivity performance. The findings suggest that the elasticity of capital stock elasticity (Capital) of production is positive and does not differ considerably, 0.44 and 0.46 respectively for low- and middle-income countries. We find that there are in general increasing returns to scale in middle-income countries and,

on the contrary, decreasing returns to scale in the low-income group at a 95 per cent significant level. Firms with higher utilization of resources and production capacity are more productive in both groups. And it is reflected by the highly significant coefficients of Capacity.

Table 4. 5 PROD approach. OLS regression of equation (4.2) results with and without interaction term

Productivity	Without interaction		With interaction	
	Low-income countries	Middle-income countries	Low-income countries	Middle-income countries
Capital	0.443*** 0.020	0.469*** 0.007	0.443*** 0.020	0.468*** 0.007
Labor	-0.103** 0.044	0.064*** 0.016	-0.102*** 0.044	0.064*** 0.016
Capacity	0.517*** 0.139	0.514*** 0.054	0.522*** 0.139	0.511*** 0.054
Exporter	0.548*** 0.073	0.205*** 0.026	0.541*** 0.074	0.204*** 0.026
Finance_obs	-0.153*** 0.053	-0.105*** 0.024	-0.152*** 0.053	-0.105*** 0.024
Infra_obs	0.055 0.051	-0.013 0.022	0.056 0.051	-0.013 0.022
Regu_obs	0.045 0.056	0.084*** 0.023	0.044 0.056	0.084*** 0.023
MAKE	0.015 0.057	0.160*** 0.024	-0.074 0.082	0.207*** 0.045
BUY	0.183*** 0.051	0.041* 0.023	0.133** 0.061	0.057** 0.027
MAKE&BUY			0.156 0.104	-0.064 0.051
Size_medium	0.364*** 0.077	0.225*** 0.034	0.369*** 0.077	0.224*** 0.034
Size_large	0.510*** 0.158	0.318*** 0.058	0.515*** 0.158	0.319*** 0.058
Constant	0.494*** 0.177	0.620*** 0.075	0.512*** 0.178	0.616*** 0.075
Obs.	1705	7381	1705	7381
Adj_R2	0.379	0.5434	0.3794	0.5434

Note: "No make or buy" is the base category. Industry, country dummies are included.

*** Significant level 1%, ** at 5%, * at 10%.

Not surprisingly, when firms face severe obstacles in their production process, their production performance is likely to be hampered or delayed and the productivity performance is expected to be lower. Financial constraints (Finance_obs) depress productivity of firms in both groups, especially in the low-income countries, the estimated coefficient being -0.153 and -0.105 respectively. Infra_obs does not differ significantly from zero in both groups. The estimated coefficients of Regu_obs show a

positive impact on the productivity across firms in middle-income countries. It might be due to the fact that firms that face more regulations are more likely to spend more time in dealing with the regulation authorities (Mohnen and Röller, 2005). As a result, they may learn how to overcome these barriers more efficiently and benefit in terms of productivity performance. It may also be that obstacles are better perceived by more innovating firms, in which case obstacles might reflect innovation with more innovating firms being more productive. Exporting firms in low- and middle-income countries are respectively 54.8 per cent and 20.5 per cent more productive than non-exporting firms. Entering international markets may enable these firms to boost their productivity by interacting with buyers and by coping with intensive competition in the export market.

Regarding the effect of innovation sourcing strategies in firms' performance, the results of Table 4.5 present us the marginal contribution of MAKE, BUY and their interaction effect. Regardless of whether the interaction term is included or not, the estimators for BUY are all positive and significant in both groups. Especially for low-income countries, firms adopting external technological sourcing are more productive compared with those that participate in in-house R&D and those that are not involved in any innovation investment. The result implies that in the context of a low level of development, firms investing in innovation through external channels are more productive and external sourcing strategies play a critical role in contributing to their performance. However, in the case of middle-income countries, in-house R&D becomes significant.

Turning to the potential synergistic effects between MAKE and BUY, the last two columns of Table 4.5 show that interaction coefficients of MAKE and BUY are not significant in both groups. This result suggests that there is no complementarity observed between MAKE and BUY in fostering productivity. The return of adopting in-house R&D and external technology buying together does not differ from the sum of the returns from adopting them individually. Assuming there are no unobserved factors across firms, we can conclude at this stage that no complementarity is confirmed between MAKE and BUY. With the presence of an interaction term, external sourcing still plays a significant role across low-income countries while investing in in-house R&D seems to be more efficient in fostering productivity improvements across firms in middle-income countries.

Practically, it is very difficult for economists to identify and control all the possible

sources of heterogeneity across firms. So far our estimations of complementarity (or substitutability) are based on the assumption that no unobserved heterogeneities exist in the returns to MAKE and BUY. This assumption will be released in the next section. The Miravete and Pernías approach will enable us to distinguish complementarity and the association due to unobserved heterogeneity.

4.5.2 The Miravete and Pernías approach

The first two columns of Table 4.6 give the bivariate probit results of conditional correlation between internal and external innovation sourcing. The bivariate probit analysis assumes no synergy ($\delta_{bm} = 0$ in equation (4.8)). After controlling for observed heterogeneities, the magnitude of the correlation coefficients between MAKE and BUY decisions do not differ much from the simple Pearson correlation coefficients that we obtained at the beginning of our analysis.

The last two columns of Table 4.6 report the results from MP approach. In the presence of complementarity and correlation due to unobserved heterogeneities, the estimated coefficients of the exogenous variables are in line with those of the bivariate probit estimation but slightly different in magnitudes. In the interpretation underlying equation (4.8) these variables explain the adoption of MAKE and BUY and their marginal return.

The firm specific factors exert a significant influence on firms' knowledge sourcing strategies. Firms with more employees seem to be more motivated to participate in both in-house and external innovating activities. Large firms are likely to have more resources to dedicate to innovation activities. Since in joint ventures technologies remain controlled by the foreign company headquarters abroad, foreign-invested companies are reluctant to engage in innovation activities by themselves. The estimated coefficients of Foreign-owner are negative but only significant in affecting MAKE for the group of middle-income countries.

Table 4. 6 Miravete and Pernías approach. MLE results

	no complementarity		Complementarity	
	Low-income countries	Middle-income countries	Low-income countries	Middle-income countries
BUY				
Foreign_owner	0.204 <i>0.140</i>	-0.111* <i>0.063</i>	0.204 <i>0.140</i>	-0.087 <i>0.060</i>
ISO	-0.078 <i>0.110</i>	0.063 <i>0.045</i>	-0.078 <i>0.110</i>	0.047 <i>0.042</i>
Internet	0.137 <i>0.093</i>	0.349*** <i>0.034</i>	0.137 <i>0.093</i>	0.281*** <i>0.039</i>
Co_supply/client	-0.322*** <i>0.070</i>	-0.223*** <i>0.036</i>	-0.322*** <i>0.070</i>	-0.232*** <i>0.033</i>
Co_university	-0.261 <i>0.194</i>	-0.366*** <i>0.101</i>	-0.261 <i>0.194</i>	-0.373*** <i>0.094</i>
Edu_manager	-0.037 <i>0.067</i>	0.288*** <i>0.034</i>	-0.037 <i>0.067</i>	0.285*** <i>0.032</i>
Size_Medium	0.063 <i>0.072</i>	0.245*** <i>0.041</i>	0.063 <i>0.072</i>	0.208*** <i>0.041</i>
Size_Large	0.258** <i>0.102</i>	0.324*** <i>0.048</i>	0.258*** <i>0.102</i>	0.262*** <i>0.049</i>
Constant	0.100 <i>0.092</i>	-0.063 <i>0.060</i>	0.100 <i>0.092</i>	-0.037 <i>0.058</i>
MAKE				
Foreign_owner	-0.202 <i>0.147</i>	-0.205*** <i>0.063</i>	-0.202 <i>0.147</i>	-0.201*** <i>0.064</i>
ISO	0.102 <i>0.109</i>	0.058 <i>0.044</i>	0.102 <i>0.109</i>	0.040 <i>0.045</i>
Internet	0.064 <i>0.095</i>	0.513*** <i>0.035</i>	0.064 <i>0.095</i>	0.452*** <i>0.041</i>
Co_supply/client	-0.069 <i>0.073</i>	0.171*** <i>0.037</i>	-0.069 <i>0.073</i>	0.193*** <i>0.038</i>
Co_university	-0.281 <i>0.222</i>	0.326*** <i>0.105</i>	-0.281 <i>0.222</i>	0.383*** <i>0.108</i>
Training	0.069 <i>0.086</i>	0.530*** <i>0.037</i>	0.069 <i>0.086</i>	0.541*** <i>0.037</i>
Size_Medium	0.287*** <i>0.077</i>	0.243*** <i>0.048</i>	0.287*** <i>0.077</i>	0.184*** <i>0.052</i>
Size_Large	0.336*** <i>0.107</i>	0.331*** <i>0.053</i>	0.336*** <i>0.107</i>	0.256*** <i>0.059</i>
Constant	-0.450*** <i>0.091</i>	-1.679*** <i>0.070</i>	-0.450*** <i>0.091</i>	-1.776*** <i>0.074</i>
Complementarity			0.000 <i>0.004</i>	0.279*** <i>0.084</i>
Correlation	0.035 <i>0.043</i>	0.101*** <i>0.022</i>	0.035 <i>0.043</i>	-0.198** <i>0.089</i>
obs.	1705	7381	1705	7381
Likelihood ratio	-2069.274	-8311.584	-2069.2744	-8306.2234

Note: Industry dummies are included. *** Significant level 1%, ** at 5%, * at 10%.

Firms with more technological capability earn more profit from adopting either of the two innovation strategies. This effect is reflected in the coefficients of the technological variables. In the middle-income countries, IT and Edu_manager are positively correlated with BUY whereas IT and Training encourage firms to adopt in-house R&D. ISO coefficients are not significant anywhere and for the low-income group, none of the technological indicators is significant. Co-operative activities, (Co_supplier/customer and Co_university) are observed to stimulate firms' MAKE decision in the middle-income countries and to reduce the purchase of external knowledge in the low-income countries.

Collaboration seems to enhance knowledge, encourage own R&D efforts and reducing the need for external knowledge, substituting in a sense for technology purchasing. After including the complementarity coefficient in the system, the correlation coefficient between residuals is unchanged and insignificant in the low-income countries as it shown in δ_{bm} , the correlation coefficient between the unobserved effects remains, insignificant in the low-income countries and becomes negative in the middle-income countries. No sign of complementarity exists in low-income countries. However, in the middle-income countries the complementarity coefficient is positive and statistically significant at the 99 per cent confidence level. Hence in those countries it pays to do both MAKE and BUY simultaneously as is generally found in developed countries.

4.6 Conclusion

The lack of advanced technological competencies in developing countries requires innovation to occur through the absorption of existing knowledge and the adoption of existing technologies. In the least developed countries, the low levels of technological capability severely constrains firms in their efforts to build up their own R&D stock of knowledge and make them rely instead on external knowledge acquisitions such as licensing, hiring skilled labor and purchasing technology embedded in machinery and collaborating with foreign firms. Our results highlight the significant contribution of external technological sourcing for productivity performance in the low-income countries. In the middle-income countries it is the combination of internal R&D and external knowledge acquisition that leads to better productivity performance.

These findings suggest that at different levels of development, governments formulate different policies in order to achieve optimal productivity performance. At a low level of

development, external sourcing strategies are essential for local firms to integrate the global market. Governments should develop policies that encourage external sourcing, such as providing technological information and financial support for technology import. In middle-income countries, where firms have sufficiently built up their technological capabilities and gathered enough innovation experience, government policies should focus on encouraging firms to invest in both internal and external technological sourcing because of the existence of a complementarity between them. This finding is consistent with the conclusion drawn from chapter 3, which suggests that a certain level of innovation capability, such as prior accumulated R&D, may be necessary for firms to utilize external know-how and for the existence of synergetic effect.

By adopting three different methods in the empirical analysis, heterogeneous results are exhibited. Due to its several limitations (see chapter 4.3), the CORR approach is suggested to apply as an auxiliary text. PROD is an effective approach to test complementarity if there is no unobserved heterogeneity correlated with potential complementary strategies. PROD is also likely to produce consistent results by incorporating with panel analysis, which can effectively control for the endogeneity. In a cross-sectional analysis, it might deliver false results as shown from our results. MP approach is suggested since it allows the separate identification of a complementarity and the unexplained correlation between the error terms.

Appendix 4A Likelihood function

$$l_i(y_{bi}, y_{mi}) = \int_{S(y_{bi}, y_{mi})} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \quad (4.a1)$$

We normalize the standard deviations of y_{bi} and y_{mi} to be equal to 1, $\sigma_b = \sigma_m = 1$. Hence, the likelihood function can be written as follows:

1) when $\delta = 0$, the likelihood function will be correspond to the likelihood function of a standard bivariate probit

$$\begin{aligned} l_i(y_{bi} = 1, y_{mi} = 1) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{\lambda_{bi}}{\sigma_b}, \frac{\lambda_{mi}}{\sigma_m}; \rho_{bm}\right) \end{aligned} \quad (4.a2)$$

$$\begin{aligned} l_i(y_{bi} = 0, y_{mi} = 0) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{-\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}}{\sigma_m}; \rho_{bm}\right) \end{aligned} \quad (4.a3)$$

$$\begin{aligned} l_i(y_{bi} = 1, y_{mi} = 0) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}}{\sigma_m}; -\rho_{bm}\right) \end{aligned} \quad (4.a4)$$

$$\begin{aligned} l_i(y_{bi} = 0, y_{mi} = 1) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{-\lambda_{bi}}{\sigma_b}, \frac{\lambda_{mi}}{\sigma_m}; -\rho_{bm}\right) \end{aligned} \quad (4.a5)$$

2) when $\delta < 0$, inequalities marked with asterisks of D(1,0) and D(1,0) in (10) are binding. The probability distribution will no longer be rectangular as the case of a bivariate probit.

$$\begin{aligned} l_i(y_{bi} = 1, y_{mi} = 1) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{\lambda_{bi} + 2\delta}{\sigma_b}, \frac{\lambda_{mi} + 2\delta}{\sigma_m}; \rho_{bm}\right) \end{aligned} \quad (4.a6)$$

$$\begin{aligned} l_i(y_{bi} = 0, y_{mi} = 0) &= \int_{\sigma_b}^{+\infty} \int_{\sigma_m}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\ &= \Phi_2\left(\frac{-\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}}{\sigma_m}; \rho_{bm}\right) \end{aligned} \quad (4.a7)$$

$$\begin{aligned}
l_i(y_{bi} = 1, y_{mi} = 0) &= \int_{-\frac{\lambda_{bi}}{\sigma_b}}^{+\infty} \int_{\frac{\lambda_{mi}+2\delta}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} - \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}+2\delta}{\sigma_m}} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}-2\delta}{\sigma_m}; -\rho_{bm}\right) - \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}+2\delta}{\sigma_m}} \Phi\left(\frac{\varepsilon_{bi}}{\sigma_b}\right) [\Phi\left(\frac{\lambda_{bi}-\lambda_{mi}+\varepsilon_{bi}}{\sigma_m}\right) - \Phi\left(\frac{-\lambda_{mi}-2\delta}{\sigma_m}\right)] d\frac{\varepsilon_{bi}}{\sigma_b}
\end{aligned} \tag{4.a8}$$

$$\begin{aligned}
l_i(y_{bi} = 0, y_{mi} = 1) &= \int_{\frac{\lambda_{bi}+2\delta}{\sigma_b}}^{+\infty} \int_{\frac{\lambda_{mi}}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} + \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}+2\delta}{\sigma_m}} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{-\lambda_{bi}-2\delta}{\sigma_b}, \frac{\lambda_{mi}}{\sigma_m}; -\rho_{bm}\right) + \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}+2\delta}{\sigma_m}} \Phi\left(\frac{\varepsilon_{bi}}{\sigma_b}\right) [\Phi\left(\frac{\lambda_{bi}-\lambda_{mi}+\varepsilon_{bi}}{\sigma_m}\right) - \Phi\left(\frac{-\lambda_{mi}}{\sigma_m}\right)] d\frac{\varepsilon_{bi}}{\sigma_b}
\end{aligned} \tag{4.a9}$$

3) when $\delta > 0$, inequalities marked with asterisks of D(1,1) and D(0,0) in (4.10) are binding.

$$\begin{aligned}
l_i(y_{bi} = 1, y_{mi} = 1) &= \int_{-\frac{\lambda_{bi}}{\sigma_b}}^{+\infty} \int_{\frac{-\lambda_{mi}-2\delta}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} - \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{\lambda_{bi}+2\delta}{\sigma_b}, \frac{\lambda_{mi}+2\delta}{\sigma_m}; \rho_{bm}\right) - \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}} \Phi\left(\frac{\varepsilon_{bi}}{\sigma_b}\right) [\Phi\left(\frac{-\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}\right) - \Phi\left(\frac{-\lambda_{mi}-2\delta}{\sigma_m}\right)] d\frac{\varepsilon_{bi}}{\sigma_b}
\end{aligned} \tag{4.a10}$$

$$\begin{aligned}
l_i(y_{bi} = 0, y_{mi} = 0) &= \int_{\frac{\lambda_{bi}}{\sigma_b}}^{+\infty} \int_{\frac{\lambda_{mi}}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} + \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{-\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}}{\sigma_m}; \rho_{bm}\right) + \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}} \Phi\left(\frac{\varepsilon_{bi}}{\sigma_b}\right) [\Phi\left(\frac{-\lambda_{bi}-\lambda_{mi}-2\delta-\varepsilon_{bi}}{\sigma_m}\right) - \Phi\left(\frac{-\lambda_{mi}}{\sigma_m}\right)] d\frac{\varepsilon_{bi}}{\sigma_b}
\end{aligned} \tag{4.a11}$$

$$\begin{aligned}
l_i(y_{bi} = 1, y_{mi} = 0) &= \int_{-\frac{\lambda_{bi}}{\sigma_b}}^{+\infty} \int_{\frac{\lambda_{mi}+2\delta}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{\lambda_{bi}}{\sigma_b}, \frac{-\lambda_{mi}-2\delta}{\sigma_m}; -\rho_{bm}\right)
\end{aligned} \tag{4.a12}$$

$$\begin{aligned}
l_i(y_{bi} = 0, y_{mi} = 1) &= \int_{\frac{\lambda_{bi}+2\delta}{\sigma_b}}^{+\infty} \int_{\frac{\lambda_{mi}}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; -s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} \\
&= \Phi_2\left(\frac{-\lambda_{bi}-2\delta}{\sigma_b}, \frac{\lambda_{mi}}{\sigma_m}; -\rho_{bm}\right)
\end{aligned} \tag{4.a13}$$

Alternatively, the likelihood function can be written as:

$$q_{ji} = 2y_{ji} - 1 (j = b, m) \tag{4.a14}$$

$$s_i = q_{bi} q_{mi} \tag{4.a15}$$

$$v_i = (s_i + 1) / 2 \tag{4.a16}$$

$$\begin{aligned}
l_i(y_{bi}, y_{mi}) &= \int_{\frac{-q_{bi}(\lambda_{bi}+2\delta y_{mi})}{\sigma_b}}^{+\infty} \int_{\frac{-q_{mi}(\lambda_{mi}+2\delta y_{bi})}{\sigma_m}}^{+\infty} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; s_i \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b} - q_{bi} \\
&\quad * 1(s_i 2\delta > 0) \int_{\frac{-\lambda_{bi}}{\sigma_b}}^{\frac{-\lambda_{mi}+s_i \lambda_{bi}+v_i 2\delta+s_i \varepsilon_{bi}}{\sigma_m}} \phi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b}
\end{aligned} \tag{4.a17}$$

$$\begin{aligned}
 &= \Phi_2\left(\frac{q_{bi}(\lambda_{bi} + 2\delta y_{mi})}{\sigma_b}, \frac{q_{mi}(\lambda_{mi} + 2\delta y_{bi})}{\sigma_m}; s_i \rho_{bm}\right) \\
 &\quad - q_b * 1(s_i 2\delta > 0) \int_{\frac{-(\lambda_{bi} + 2\delta)}{\sigma_b}}^{\frac{-\lambda_{bi}}{\sigma_b}} \int_{\frac{-(\lambda_{mi} + 2\delta y_{bi})}{\sigma_m}}^{\frac{-(\lambda_{mi} + s_i \lambda_{bi} + v_i 2\delta + s_i \varepsilon_{bi})}{\sigma_m}} \varphi_2\left(\frac{\varepsilon_{bi}}{\sigma_b}, \frac{\varepsilon_{mi}}{\sigma_m}; \rho_{bm}\right) d\frac{\varepsilon_{mi}}{\sigma_m} d\frac{\varepsilon_{bi}}{\sigma_b}
 \end{aligned}$$

Appendix 4B Truncated bivariate probit with upper and lower bounds and the GHK simulator

$$\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \sim TN(\mu, \Sigma; a, b) \equiv N(\mu, \Sigma) \text{ s.t. } a < \varepsilon < b \quad (4.b1)$$

L be the lower triangular Cholesky factorization of Σ with elements

$$\begin{pmatrix} l_{11} & 0 \\ l_{21} & l_{22} \end{pmatrix}$$

Let (v_1, v_2) denote a vector of independent truncated standard normal random variables with upper truncation and lower truncation point. Then we can derive (4.b1) as:

$$\left\{ \begin{array}{l} \frac{a_1 - \mu_1}{l_{11}} < v_1 < \frac{b_1 - \mu_1}{l_{11}} \\ \frac{a_2 - \mu_1 - l_{21}v_1}{l_{22}} < v_2 < \frac{b_2 - \mu_1 - l_{21}v_1}{l_{22}} \end{array} \right. \quad (4.b2)$$

The above suggests that we can draw (v_1, v_2) recursively. In order to do so, we first use z_i ($i = 1, 2$) to represent the draw from truncated standard normal random variables ($\mu = 0$), and

$$z_1 = \Phi_i\left(\frac{b_1}{l_{11}}\right) - \Phi_i\left(\frac{a_1}{l_{11}}\right). \text{ Then we can generate } v_1 \text{ from} \quad (4.b3)$$

$v_1 = \Phi_i^{-1}(z_1)$. And we can draw z_2 in the same way,

$$z_2 = \Phi_i^{-1}\left(\frac{b_2 - l_{21}v_1}{l_{22}}\right) - \Phi_i^{-1}\left(\frac{a_2 - l_{21}v_1}{l_{22}}\right) \quad (4.b4)$$

Hence, the truncated bivariate probability can be written as:

$$\begin{aligned} & \text{Prob}(a_1 < \varepsilon_1 < b_1) \text{Prob}(a_2 < \varepsilon_2 < b_2 \mid a_1 < \varepsilon_1 < b_1) \\ &= \text{Prob}\left(\frac{a_1}{l_{11}} < v_1 < \frac{b_1}{l_{11}}\right) \text{Prob}\left(\frac{a_2 - l_{21}v_1}{l_{22}} < v_2 < \frac{b_2 - l_{21}v_1}{l_{22}}\right) \\ & \text{Prob}_{GHK} = \frac{1}{D} \left[\Phi\left(\frac{b_1}{l_{11}}\right) - \Phi\left(\frac{a_1}{l_{11}}\right) \right] * \left[\Phi\left(\frac{b_2 - l_{21} * [\Phi_i^{-1}(z_1)]}{l_{22}}\right) - \Phi\left(\frac{a_2 - l_{21} * [\Phi_i^{-1}(z_1)]}{l_{22}}\right) \right] \end{aligned} \quad (4.b5)$$

Chapter 5

Statistical inference with multiple inequality restrictions

5.1 Introduction

Statistical inferences with inequality (one-sided) restrictions arise frequently in complementarity studies. Inequality restrictions are often imposed on model parameters due to the potential complementary or substitutive relationships between explanatory variables.

When one tries to test complementarity among three or more activities in a linear model, multiple inequality restrictions are imposed to the estimated parameters and the corresponding statistical inference will be based on multivariate one-sided hypotheses. Tests of complementarity based on inequality restrictions have been discussed in several previous studies (Mohnen and Röller, 2005; Lokshin et al., 2007; Carree et al., 2011). However, little has been written regarding the validity of these hypotheses. In particular, very little research has been done on the one-sided restricted inferences for models with more than two potential complementary/substitutive activities. This chapter attempts to fill this gap.

The empirical analysis uses simulated datasets to demonstrate how different types of hypotheses are used for testing complementarity. The findings reveal the biases that potentially exist in different types of multivariate one-sided tests of complementarity. The results try to explain which hypothesis is preferable across different sample sizes and values of goodness of fit.

The next section reviews previous relevant studies and explains the one-sided tests of hypotheses in models with multiple inequality constraints. Section 5.3 introduces the data drawing process and compares the results generated from different types of hypotheses. The conclusion will be drawn in the last section.

5.2 Complementarity with more than two activities

5.2.1 Definition of pairwise complementarity

Suppose there are two activities x_i, x_j and Z is a vector of exogenous variables. The objective function $f(x_i, x_j, Z)$ is supermodular if for all values of $x_1, \dots, x_n$, at least one of the following inequality holds:

$$\frac{\partial^2 f(x_i, x_j, Z)}{\partial x_i \partial x_j} > 0 \quad (\text{if } x \text{ is continuous term}) \quad (5.1)$$

$$f(x_i = 1, x_j = 1 | Z) + f(x_i = 0, x_j = 0 | Z) - f(x_i = 1, x_j = 0 | Z) - f(x_i = 0, x_j = 1 | Z) > 0$$

$$(\text{if } x \text{ is dichotomous term}) \quad (5.2)$$

x_i and x_j are complements if one activity x_i in the objective function increases conditional on the increase of another activity x_j , for inequality function (5.1), or the presence of one activity x_i increases the marginal return of another activity x_j , for inequality function (5.2), in both cases controlling for other exogenous effects. In the case of substitutability, the inequality signs are reversed.

In order to build up a clear methodology to empirically test the complementary relationship among two or more economic activities, two types of complementarity are distinguished: “objective complementarity” and “behavioral complementarity” (see chapter 2 for more details). Regarding the testing methods, two approaches have been adopted⁵¹. The “Production approach” (PROD) is broadly used in estimating “objective complementarity” by looking at the estimated cross-term coefficients in the objective function (Mohnen and Röller, 2005; Belderbos, 2004; Cassiman and Veugelers, 2006). The “Correlation approach” (CORR) uses the pairwise correlation coefficients after controlling for the firm specificities to identify the complementary/substitutive relationship between two activities. This approach is adopted to test the “behavioral

⁵¹ Here we only look at the complementarity among activities that are dichotomous choices.

complementarity” since the estimation is only based on the adoption decisions without involving an objective function. A recently developed approach introduced by Miravete and Pernías (Miravete and Pernías, 2006; Kretschmer, et al., 2012) has been adopted to test for “behavioral complementarity” and can be classified somewhere between the PROD approach and CORR approach. The authors try to estimate the choice equations together with an objective function (see chapter 4.3 for more details).

When one tries to test complementarity among three or more activities, the CORR approach can be implemented in a multivariate framework (Arora and Gambardella, 1990; Belderbos et al., 2006; Tether and Tajar, 2008; Schmiedeberg, 2008). For the PROD approach, it is more complicated because it involves estimation with multiple inequality restrictions imposed on coefficients. Incorporating only the cross-term of two activities one by one in the objective equation (Single cross-term)⁵² or including all pairwise cross-terms (All cross-term)⁵³ is likely to generate biased estimation due to the fact that these two structures ignore the cross-partial effects between extra activities and the cross-terms of higher-order interactions (e.g. the third-order, the fourth-order etc.)⁵⁴.

5.2.2 Studies of complementarity with more than two activities

The nature of complementarity makes it appealing to researchers who intend to investigate synergies among economic activities, strategies and policies. The methodology of testing for complementarity has been broadly applied in empirical studies after it was first introduced in economics by Edgeworth (1881) and further developed by Milgrom and Roberts (1990a; 1995). Table 5.1 below summarizes representative empirical innovation related studies in testing complementarity for cases of more than two activities or strategies. As shown in column 6, most previous studies are either using the “All cross-term” or the “Single cross-term” approach by ignoring the full cross-term specification, which are the interaction terms of third- or higher-order.

The study of complementarity between innovation policies conducted by Mohnen and Röller (2005) adopted the full cross-term function. Similarly, Belderbos et al. (2006) adopted the same specification in testing complementarity among four co-operative activities of a firm. The difference between these two studies lies in the statistical

⁵² See example from Bresnahan et al. (2002); Black and Lynch (2001); Lokshin et al. (2007)

⁵³ See example from Caroli and Van Reenen (2001); Lokshin et al. (2010)

⁵⁴ Lokshin et al. (2007) and Carree et al. (2011) provide an excellent review.

inference with multiple inequality restrictions. The multivariate one-sided hypotheses are defined differently. The former study uses strictly complementarity hypothesis $H_1: R\beta > r$ vs $H_1: R\beta! > r$ (! denotes “not”) while the latter uses non-strictly complementarity hypothesis $H_0: R\beta = r$ vs $H_1: R\beta \geq r$. The hypothesis testing methods adopted in these two studies are Wald test and Likelihood Ratio test respectively. Gouriéroux et al. (1982) explained these two methods in linear model with inequalities constraints, and they found out that the relationship between the likelihood ratio test and the Wald test are the same as in the equality constrained case.

Table 5. 1 Complementarity in innovation studies with more than two activities or strategies

Study by	Data	Dependent variables	Activities/strategies	No of activities	Method	Findings
Arora and Gambardella, 1990	US, European, and Japanese chemical and pharmaceutical producers, 1978-1988	External linkages	External linkages (firm, university, third party and external sourcing)	4	CORR (conditional correlation)	The strategies are positively correlated even after controlling for firm-specific characteristics.
Parthasarathy and Sethi, 1993	87 Flexible automation user	Flexible automation	Various strategy and structure choices	6	PROD (Single cross-term)	Some complements while some substitutes
Ichniowski, Shaw and Prennushi, 1997	36 homogeneous steel production lines, monthly panel data	Productivity	Organizational and human resource practices	5	PROD (All cross-term)	Complementary
Love and Roper, 1999; 2001	Product Development Survey (PDS): UK, German and Irish plants, 1994	Innovation intensity; Innovation success	R&D, tech transfer and network	3	PROD (Single cross-term)	Complementarity found in the case of UK and Ireland
Damijan et al., 2003	Firm-level data for eight transition countries, 1994–1998	Total factor productivity	FDI, R&D and tech importing	3	PROD (All cross-term)	
Yannis et al., 2004	Greece, Italy, Denmark, UK, France, Germany and the Netherlands, 558 innovative firms, 2000	Innovation intensity	Openness, R&D and human resources training	3	PROD (All cross-term)	Both internal capabilities and openness are complementary for innovative performance
Mohnen and Röller, 2005	CIS ⁵⁵ 1 survey data from four countries: Ireland, Denmark, Germany, and Italy.	Innovation intensity; Innovation success	Four kinds of obstacles to innovation	4	PROD (Full cross-term Wald test)	A package of policies will make firms innovate.
Hu et al., 2005	Large and medium size enterprises, 1995-1999	Productivity	R&D, technology transfer and FDI	3	PROD (All cross-term)	R&D complements technology transfer
Belderbos et al., 2006	Netherlands CIS, 1996 and 1998	Productivity growth	Four types of cooperation partners	4	PROD (Full cross-term LR test)	The joint adoption of cooperation strategies is preferred.
Li, 2011	Large and Medium size SOEs in high-tech industry, 1995-2004	Number of patent	R&D, domestic technology and foreign technology	3	PROD (Single cross-term)	Imported technology leveraged by R&D

⁵⁵ Community Innovation Surveys.

5.2.3 Modeling complementarity in a linear function

Consider the linear model

$$y = X\beta + u \quad (5.3)$$

where y is a $(n \times 1)$ vector, X is a $(n \times k)$ matrix, and β is a $(k \times 1)$ vector. u is an $(n \times 1)$ dimension vector following a normal distribution $N(0, \Omega)$, where Ω is the variance-covariance matrix. Let q denote the number of activities. A full cross-term specification for 3 and 4 activities is expressed respectively⁵⁶ as

$$y_{q=3} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{23} x_2 x_3 + \beta_{123} x_1 x_2 x_3 + u \quad (5.4)$$

$$y_{q=4} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + \beta_{34} x_3 x_4 + \beta_{123} x_1 x_2 x_3 + \beta_{124} x_1 x_2 x_4 + \beta_{234} x_2 x_3 x_4 + \beta_{1234} x_1 x_2 x_3 x_4 + u. \quad (5.5)$$

For the case where x is continuous, the cross derivative $\partial^2 y / \partial x_i \partial x_j$ will be used to test for complementarity between x_1 and x_2 . It equals to $\beta_{12} + \beta_{123} x_3$ for equation (5.4) and $\beta_{12} + \beta_{123} x_3 + \beta_{124} x_4 + \beta_{1234} x_3 x_4$ for equation (5.5).

The current study focuses on cases where x is dichotomous. According to (5.2), x_1 and x_2 are complementary activities only if at least one of the inequality conditions holds for each

$$q=3 \left\{ \begin{array}{l} f_{\text{complement}}(x_1, x_2 | x_3 = 0) = \beta_{12} \geq 0 \\ f_{\text{complement}}(x_1, x_2 | x_3 = 1) = \beta_{12} + \beta_{123} \geq 0 \end{array} \right. \quad (5.6)$$

$$q=4 \left\{ \begin{array}{l} f_{\text{complement}}(x_1, x_2 | x_3 = 0, x_4 = 0) = \beta_{12} \geq 0 \\ f_{\text{complement}}(x_1, x_2 | x_3 = 1, x_4 = 0) = \beta_{12} + \beta_{123} \geq 0 \\ f_{\text{complement}}(x_1, x_2 | x_3 = 0, x_4 = 1) = \beta_{12} + \beta_{124} \geq 0 \\ f_{\text{complement}}(x_1, x_2 | x_3 = 1, x_4 = 1) = \beta_{12} + \beta_{123} + \beta_{124} + \beta_{1234} \geq 0 \end{array} \right. \quad (5.7)$$

⁵⁶ We only give example of $q=3$ and $q=4$. For cases where $q>4$, the specification can be easily expanded based on the definition given.

The inverse inequality sign for (5.6) and (5.7) will indicate a substitutive relationship between x_1 and x_2 ⁵⁷.

The procedure of testing for complementarity follows three steps⁵⁸. First, construct the objective function. Whether the objective function is well specified will directly influence the power of the test. The indicator R-square (goodness of fit) in OLS can be used to measure the quality of the model specification. The linear specification (5.3) will be used for the current study. Another important factor influencing the statistical power of the test is the number of observations. A larger sample is likely to generate more precise results.

Second, once the objective function is specified, one can define estimators associated with inequality constraints (5.6) and (5.7) for $q=3$ and $q=4$ respectively. We assume the unconstrained estimator is $\bar{\beta}$ and the inequality constrained estimator $\hat{\beta}_r$ is the solution of

$$\begin{aligned} &\max - (y - X\beta)' \Omega^{-1} (y - X\beta) \\ &\text{subject to (5.6) or (5.7)} \end{aligned} \tag{5.8}$$

where Ω , the variance–covariance matrix of the error term, can be consistently estimated by $\bar{\Omega}$ ⁵⁹. Function (5.8) is a quadratic form which can be solved by several algorithms (e.g Judge and Takayama, 1966; Liew, 1976; Gourieroux et al., 1982).

The third step uses either the likelihood ratio test (Gourieroux, Holly et al., 1982) or the Wald test (Kodde and Palm, 1986) to check the statistical significance of coefficients with inequality constraints.

5.2.4 The multivariate one-sided hypotheses

In the following discussions, we assume that the error term in the linear equation (5.3) follows a normal distribution. The different types of one-sided hypotheses in connection with complementarity are (“!” denotes “not”)⁶⁰:

⁵⁷ The prior literature (Athey and Stern, 1998; Mohnen and Röller, 2005) denotes x_1 and x_2 as “strictly complementarity” if the inequalities in (5.6) and (5.7) are strict inequalities.

⁵⁸ These procedures only apply for testing “objective complementarity”.

⁵⁹ $\bar{\Omega}$ and $\bar{\beta}$ can be obtained by ML, OLS or GLS.

Hypothesis Test 1 (HT1) $H_0 : R\beta = 0$ vs $H_1 : R\beta \geq 0$

Hypothesis Test 2 (HT2) $H_0 : R\beta \geq 0$ vs $H_1 : R\beta \not\geq 0$

R is a matrix with dimension of $(p \times k)$ which defines the imposed inequality restrictions on the estimated parameters, p being the number of inequality constraints that have to be tested simultaneously. In the case of more than two activities, p will be equal to 2^{q-2} . HT1 (Hypothesis Test 1) tests equality against at least one inequality holding. Rejecting the null of HT1 suggests the existence of complementarity. HT2 (Hypothesis Test 2) tests if all $R\beta$ are greater or equal to zero against at least one violation in the null hypothesis (not all $R\beta$ are bigger or equal to zero). The complementarity will be concluded if we accept the null of HT2.

The potential problem with HT1: Non-exhaustiveness

One important thing should be noted here is that the HT1 is not exhaustive. It is adopted if one believes that the return of adopting activities simultaneously should be at least as high as adopting them individually. In the absence of exhaustiveness, what happens if the true parameter value is in the region which is not covered by either the null or the alternative hypothesis? For example, $R\beta < 0$. In this case, HT1 would be misleading and the test at the α level of confidence will be biased in favour of the null. Grömping (2010) explained the potential problem as: “interpretation of test results in multiple inequality restrictions should take into account the a-priori nature of the restriction, and one must realize that the only guaranteed null hypothesis is the stated null hypothesis”⁶¹. In the current research of complementarity between economic activities, rejecting HT1 indicates at least one violation of the equality conditions. It does not guarantee that all inequalities are positive. The first row from Table 5.2 illustrates all possible directions of $R\beta$. In the second row of Table 5.2, the results (accepting or rejecting the null hypothesis) based on the HT1 are given. If $R\beta$ falls into the non-defining space of HT1 – “ $R\beta < 0$ ”, then the test results would suggest accepting the null.

⁶⁰ It is worthwhile to mention that, in general, the null hypothesis is based on one of these three signs: = (equal to), $\leq$ (less than or equal to), or $\geq$ (greater than or equal to). In particular, the equality is always a part of the null hypothesis and the alternative hypothesis can never include an equal sign.

⁶¹ Some other studies also addressed this issue, such as Cohen, Kemperman, and Sackrowitz (2000), Perlman and Wu (2003), and Silvapulle (1997).

Even though the conclusion drawn based on this results is correct (no complementary relationship between the explanatory variables), it is somehow a result biased in favour of the null because the acceptance of the null hypothesis is not due to the equality ($R\beta = 0$). In the last column with at least one inequality holding for both " $R\beta \leq 0$ " and " $R\beta \geq 0$ " respectively, the test result would suggest rejecting the null even if there is no existence of complementarity. In these circumstances, HT1 is misleading because it can reject the null even in cases there is no complementarity. Hence, we suggest adopting the HT1 in complementarity studies if only one has adequate reasons to believe that the values of $R\beta$ are in one direction (all non-negative or non-positive). Lokshin et al. (2007) suggested that comparing the log-likelihood ratio of different specifications would avoid the potential the non-exhaustiveness error. Firstly, this method firstly requires the model to be estimated three times: unconstrained, less or equal (" $\leq$ ") and greater or equal (" $\geq$ "). Then the one that produced the highest log-likelihood value will be used as alternative in HT1 against the equality restriction⁶².

Table 5. 2 Conditions for accepting or rejecting the Null of HT1 and HT2 in testing for complementarity

	All " $=$ "	All " $\leq$ "*	All " $\geq$ "*	Both " $\leq$ " and " $\geq$ "*
HT1 Null	Accept	Accept	Reject	Reject ^F
HT2 Null	Accept ^F	Reject	Accept	Reject

Situations with * indicates: at least one inequality holds.

Both " $\leq$ " and " $\geq$ " indicates: the results are falling into both negative and positive parts of p-dimensional space, specifically, at least one inequality holds for both " $\leq$ " and " $\geq$ ".

Superscription "F" indicates: the false conclusion in terms of complementarity.

The potential problem with HT2: there are only equality restrictions

Another important point which needs to be noted is that the null hypothesis in HT2 does not rule out the possibility of all equalities holding. Therefore, accepting the null of HT2 cannot give a concrete conclusion either. The third row of Table 5.2 describes the acceptance or rejection of the null of HT2 for different values of $R\beta$. HT2 is defined to

⁶²This method indeed simplifies the testing procedure in the sense that it does not require us to use HT2 to solve the potential bias induced by non-exhaustiveness. However, the tradeoff here is that it imposes more computation by estimating the model four times (unconstrained, less or equal (" $\leq$ "), greater or equal (" $\geq$ ") and with equality constrained). In the procedure we proposed later, which takes into account both TH1 and TH2, the model only needs to be estimated only three times (unconstrained, greater or equal (" $\geq$ ") and with equality constrained).

be exhaustive and all possible values of $R\beta$ are covered either in the null or in the alternative hypothesis. If one concludes complementarity based on the acceptance of the null in HT2, then the results are false when all values of $R\beta$ are equal to zero.

We suggest that a test procedure derived by a method that takes into account both TH1 and TH2⁶³ has a higher statistical power⁶⁴ than test procedures which take only one of the two into account. The main purpose of this chapter is to check whether TH1 or TH2 individually will also produce a satisfactory statistical power. TH1 individually means that we only take account three restrictions (unconstrained, greater or equal and equality constrained) whereas TH2 individually means only two restrictions (unconstrained, greater or equal). Focusing on only one hypothesis test will reduce the computation work substantially, especially the later one. The Monte Carlo experiment shows that, in some situations, only conducting TH1 or TH2 may generate satisfactory results. Situations associate with the sample size and the model specification.

5.2.5 The hypothesis test method: likelihood ratio test

For one-sided hypotheses, various testing methods such as likelihood ratio, Wald and score tests have been proposed⁶⁵. In the following, we provide a brief review of multivariate one-sided hypothesis testing (HT1 and HT2) for complementarity studies by using the likelihood ratio test⁶⁶.

The likelihood ratio test statistic (LRT) is defined (Greene, 2003) as

$$\xi_{LR} = -2\log\Lambda = 2(\hat{L}_1 - \hat{L}_0) \quad (5.9)$$

⁶³ More efficient results can be drawn by accepting the null hypothesis of HT2 and rejecting the null hypothesis of HT1 in testing for complementarity. Another way to produce exactly the same results is by testing either HT1 or HT2 twice, with respect to complementarity and substitutability respectively. The same as in the study by Lokshin et al. (2007), it requires the model to be estimated four times, once unconstrained, with equality constrained, with complementary restrictions and with substitutive restrictions. Specifically, two activities are complementary only if the following two conditions are satisfied: 1) rejecting (accepting) the null of HT1 (HT2) in the complementarity test; 2) accepting (rejecting) the null of HT1 (HT2) in the substitutability test. It only requires us to look at HT1 or HT2 individually. We have tried these three ways of hypothesis testing in our empirical analysis; exactly the same results were generated.

⁶⁴ The higher statistical power here indicates a higher value of sensitivity, which is used as an indicator to measure the test performance. See section 5.3.1 for more details.

⁶⁵ See Silvapulle and Sen (2004) for a detailed review.

⁶⁶ Gourieroux (1982) conducted detail comparisons of the LRT, the Wald test and the score test. The result revealed that these three hypothesis tests methods generate roughly the same results.

where $\hat{L}_1$ and $\hat{L}_0$ are the maximum value of the logarithm of the likelihood function under the alternative hypothesis H_1 and the null hypothesis H_0 . Obtaining $\hat{\beta}_1$ by maximizing (5.8), it is verified that ξ_{LR} is the optimum value of the objective function of the minimization problem (see Gouriéroux, 1982),

$$\text{HT1: } \xi_{LR} = \min[(\bar{\beta} - \hat{\beta}_0)'(X'\Omega^{-1}X)(\bar{\beta} - \hat{\beta}_0) - (\bar{\beta} - \hat{\beta}_1)'(X'\Omega^{-1}X)(\bar{\beta} - \hat{\beta}_1)] \quad (5.10)$$

$$\text{HT2: } \xi_{LR} = \min(\bar{\beta} - \hat{\beta}_1)'(X'\Omega^{-1}X)(\bar{\beta} - \hat{\beta}_1) \quad (5.11)$$

where $\bar{\beta}$ and $\hat{\beta}_0$ are unconstrained estimator and the estimator under equality constraints. $\hat{\beta}_1$ are the estimators subject to constraints (5.6) or (5.7) and $R\hat{\beta}_1$ represents the point in the nonnegative orthant that is closest to $R\bar{\beta}$ - orthogonal projection of $R\bar{\beta}$ to the null parameter space (5.6) or (5.7). Similar to the Wald-type statistic, the LRT statistics here also measures the squared “distance” between $R\hat{\beta}_1$ and $R\bar{\beta}$. Figure 5.1 is an example of three activities ($p=2$) for HT2, when $(X'\Omega^{-1}X)^{-1} = I$ (identity matrix), the projection of $R\bar{\beta}$ to the null parameter space varies depending on the location where the $R\bar{\beta}$ falls. Then $R\hat{\beta}_1$ is given as

$$\left\{ \begin{array}{ll} (0, 0) & \text{if } R\bar{\beta} \in Q_1 \\ (\beta_{12}, 0) & \text{if } R\bar{\beta} \in Q_2 \\ (\beta_{12}, \beta_{12} + \beta_{123}) & \text{if } R\bar{\beta} \in Q_3 \\ (0, \beta_{12} + \beta_{123}) & \text{if } R\bar{\beta} \in Q_4 \end{array} \right.$$

The conditional distribution is a mixture of chi-squared distributions (Gouriéroux et al., 1982; Kudo, 1963; Perlman, 1969; Kodde and Palm, 1986) which can be written respectively as

$$\Pr(\xi \geq c) = \sum_{i=0}^p \Pr[\chi^2(i) \geq c] w(p, i) \quad (5.12)$$

where $w(p, i)$ denotes the probability that i of the p elements of $R\hat{\beta}$ are strictly positive. $\chi^2(0)$ is the unit at the origin⁶⁷. c represents the critical value of the probability of the test statistics at a given level of significance⁶⁸.

Figure 5.1 Orthogonal projection of $R\bar{\beta}$ to the Null parameter space for HT2 (equation 5.6)

5.3 A comparison of HT1 and HT2 in simulation experiments

5.3.1 Data drawing process

In order to easily compare the statistical power of HT1 and HT2 in case of complementarity, the estimation will be performed on simulated data. We would like to verify (1) that HT1 yields biased results in testing complementarity and tends to overestimate the potential complementarities if one has no support to believe that the values of $R\beta$ are in one direction (all non-negative or non-positive); (2) that a test

⁶⁷ The geometrical proof can be found in Gourieroux et al. (1982).

⁶⁸ The simulations are done with statistical program R. The programming code is available upon request.

procedure that accounts for both HT1 and HT2 has a better performance; (3) that in some situations, using only one test of hypothesis can also generate satisfactory results.

Since most of the empirical studies that investigate pairwise complementarity among multiple activities use dichotomous data, the model adopted in the analysis will be based on equation (5.4) and (5.5) where X are discrete choice variables. The criteria for x_1 and x_2 to be complementary are the inequality constraints (5.6) and (5.7) for respectively 3 and 4 activities.

The sample size of the simulation experiment is set to 500, 1000 and 5000. The data generation follows the process proposed by Lokshin et al. (2007). First, elements in $(k \times 1)$ dimension vector β which follow a standard normal distribution $\sim N(0,1)$ are randomly and independently drawn. Second, construct a discrete variable matrix X composed of vector $x_1 \dots x_{123}$ ⁶⁹, which elements are set to 1 if the corresponding element in a standard multivariate random draw is positive. Third, use equation (5.4) and (5.5) to construct values of y based on x_i and β . A normally distributed residual vector will be used to indicate the explanatory power of the model specification. The variance of the residual vector is set to values 0.025, 1 and 3.25 to represent a desired R^2 ⁷⁰.

The above processes will be repeated 10,000 times. Each time, we categorize x_1 and x_2 as complementary if randomly drawn coefficients satisfy $\beta_{12} \geq 0$ and $\beta_{12} + \beta_{123} \geq 0$ with at least one inequality restriction holding strictly. It will be classified in the substitutive group if $\beta_{12} \leq 0$ and $\beta_{12} + \beta_{123} \leq 0$ with at least one inequality restriction holding strictly. The rest will be put in the inconclusive group. The inequality conditions (5.7) will be applied in the case of 4 activities.

Results of testing pairwise complementarity/substitutability among 3 activities are presented in Table 5.3 with sample size 500, 1000 and 5000 respectively. Table 5.4 gives the results for 4 activities. Statistics are generated by using the LRT⁷¹. After the regression on each draw (repetition), one set of estimated coefficients will be given.

⁶⁹ In the case of 4 activities, x_i is composed of $x_1 \dots x_{1234}$.

⁷⁰ Lokshin et al. (2007) has shown that variances of the residual equal to 0.025, 1 and 3.25 respectively represent R-squares of 0.9, 0.5 and 0.1.

⁷¹ The significant level of both tests is set at 90 per cent. We have tried with 95 and 99 per cent significant levels. Only limited change has been found. We have also performed the estimation with the Wald test. Results are almost equivalent to those with LRT.

Three types of hypotheses - HT1, HT2 and HT1&HT2 - are applied in the estimated coefficient for testing the complementarity/substitutability between two activities and hence, the conclusion will be drawn three times. The statistical results are decomposed according to their actual and tested relationships. Take the upper left panel of Table 5.3 as an example, it presents the results of 3 activities with 500 observations and R-square value of 0.9. Columns give the number of actual relationships whereas rows give the number of tested relationships after 10,000 repetitions. Statistical results are given for subcategories HT1, HT2, and HT1&HT2 respectively. Before the estimation, the actual relationship for each repetition is observed. There are in total 3740(3722+18) estimations are actual complementary, 3767(6+3761) estimations are actually substitutive and 2493(2149+344) estimations are actually neither complementary nor substitutive (None)⁷². After repeating the estimations by 10,000 times, As the row “Comple.*” and “Comple.**” shows, there are 5877(3722+6+2149)⁷³ repetitions that concluded in favor of complementarity by using HT1 and 4066(3738+24+304) cases for HT2. By using HT1&HT2, there are 3987(3720+1+266) repetitions that concluded in favor of complementarity.

Two statistical measurements are used to compare HT1, HT2 and HT1&HT2. Tables 5.5 and 5.6 are the statistics with respect to these two measurements: sensitivity and accuracy. Sensitivity measures the proportion of actual complementarities which are correct identified after 10,000 repetitions. It is calculated as True Positives⁷⁴ divided by the summation of True Positives plus False Positives. Accuracy measures the proportion of correct conclusions divided by the number of repetitions. It is calculated as the summation of True Positives plus True Negatives divided by 10,000. Take the upper left panel of Table 5.3 as an example. Under the subcategory HT1&HT2, there are in total 3987 (of which 3720 cases of actual complementarity, 1 case of actual substitutability and 266 cases of actually no relationship) out of 10,000 estimations that are concluded to have complementarity for 3 strategies with an R-square of 0.9 and 500 observations. The

⁷² The number of actual complementarity, substitutability and None are the same for the subcategory of HT1, HT2 and HT1&HT2.

⁷³ In a binary classification test, 3722 is the number of True Positives. They measure the number of actual complementarities that are correctly identified. 2155 (6+2149) is defined as False Positives. It is the number of substitutability (6) and no relationships (2149) that are incorrectly concluded as complementarity. 18 is defined as False Negative: actual complementarities incorrectly identified as “no complementarity”. 5932 (3743+2189) is defined as True Negative: “no complementarity” correctly identified as “no complementarity”.

⁷⁴ See footnote 73 for the definitions of True Positive, False Positive, True Negative and False Negative.

number of actual cases of complementarity is 3740 (the True Positives, 3720, plus the False Negatives, 20). The sensitivity is $99.47\%(3720/3740)$ and the accuracy is $97.13\%((3720+3738+1921+28+306)/10000)^{75}$.

Despite sensitivity is a commonly used statistical indicator to measure the performance of binary classification test, it only account for the proportion of actual positives which are correctly identified as such. For the present study, accuracy is more preferable in the sense that it takes into account both True Positives and True Negatives. For example, there are only slight differences in sensitivity for HT1 and HT2 in the upper left panel of Table 5.5. However, the accuracy shows that, compared with HT1, there is a much higher probability for HT2 to generate a correct conclusion. A preferable hypothesis would be described as 100% sensitive and 100% accurate. However, there is sometimes a trade-off between the measures. For instance in the lower left panel of Table 5.5, one would conclude that HT2 is better compared with HT1 based on the sensitivity whereas others might prefer HT1 rather than HT2 due to the relatively higher level of accuracy in HT1. Under such circumstances, we would prefer the hypothesis that generates higher value of accuracy.

One thing should be noted here is that the sensitivity and accuracy of “None” are not given for HT1 and HT2 because the binary classification tests have only be done with respect to complementarity/substitutability. The rejection of such relationships does not provide further information on whether there is actually no relationship.

5.3.2 Interpretation of the results

The statistical power of LRT in testing multivariate one-sided hypotheses varies with sample sizes and R-square values. As the sensitivities show in Table 5.5 and Table 5.6 more than 90% actual complementarities/substitutabilities are correctly identified for the sample with R-square above 0.5. The sensitivity declines with the decreasing R-square values. The positive correlations between the sensitivity and the R-square are observed for all three types of hypothesis settings. The same relationship is shown for the sensitivity and the number of observations - a larger sample accommodates more consistent results if the sensitivity is used as the measurement.

⁷⁵ In order to generate comparable results between HT1&HT2 and the others, the accuracy is calculated based on a binary classification test. Specifically, a complementarity test by using HT1&HT2 will only give results on “complementarity” or “no complementarity”. Therefore, there are in total 9713 cases that are classified as correct conclusions: 3720 true positives and 5993(3738+1921+28+306) true negatives.

Table 5. 3 Monte Carlo results of testing pairwise complementarity in 3 activities (10,000 repetitions): decomposition statistics

R2 =		90%								
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		3722	6	2149	3731	3	2227	3738	1	2394
No Complem.		18	3761	344	9	3764	266	2	3766	99
HT2										
Complem.**		3738	24	304	3737	11	214	3737	2	96
No Complem.		2	3743	2189	3	3756	2279	3	3765	2397
HT1&HT2										
Complem.***		3720	1	266	3728	0	178	3734	0	86
Substit.		0	3738	306	0	3749	225	0	3763	90
None		20	28	1921	12	18	2090	6	4	2317
R2 =		50%								
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		3372	24	1353	3562	14	1580	3709	6	2037
No Complem.		368	3743	1140	178	3753	913	31	3761	456
HT2										
Complem.**		3722	375	1112	3728	195	875	3735	39	426
No Complem.		18	3392	1381	12	3572	1618	5	3728	2067
HT1&HT2										
Complem.***		3359	9	666	3564	10	562	3705	2	335
Substit.		5	3377	694	4	3591	611	0	3722	368
None		376	381	1133	172	166	1320	35	43	1790
R2 =		10%								
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		1914	85	477	2366	60	646	3340	24	1260
No Complem.		1826	3682	2016	1374	3707	1847	400	3743	1233
HT2										
Complem.**		3658	1938	2014	3676	1366	1886	3715	425	1216
No Complem.		82	1829	479	64	2401	607	25	3342	1277
HT1&HT2										
Complem.***		1900	71	415	2388	69	570	3337	18	391
Substit.		68	1815	417	48	2551	537	12	3393	717
None		1772	1881	1661	1304	1147	1386	391	356	1078

Notes:

Complementarity with one asterisk (Complem.*) is concluded if the test rejects the null of HT1 in testing for complementarity.

Complementarity with two asterisks (Complem.***) is concluded if the test accepts the null of HT2 in testing for complementarity.

Complementarity with three asterisks (Complem.****) is concluded by using one of the following methods: 1) accepting the null hypothesis of HT2 and rejecting the null hypothesis of HT1 in testing the complementarity; 2) rejecting the null of HT1 in the complementarity test and accepting the null of HT1 in the substitutability test; 3) accepting the null of HT2 in the complementarity test and rejecting the null of HT2 in the substitutability test. We have tried these three ways of hypothesis testing in our empirical analysis, exactly the same results are generated.

Table 5. 4 Monte Carlo results of testing pairwise complementarity in 4 activities (10,000 repetitions): decomposition statistics

R2 = 90%										
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		2569	0	4342	2570	1	4491	2570	0	4692
No Complem.		1	2603	485	0	2602	336	0	2603	135
HT2										
Complem.**		2569	0	500	2569	1	347	2569	0	133
No Complem.		1	2603	4327	1	2602	4480	1	2603	4694
HT1&HT2										
Complem.***		2566	0	475	2569	0	334	2569	0	128
Substit.		0	2592	456	0	2593	315	0	2588	127
None		4	11	3896	1	10	4178	1	15	4572
R2 = 50%										
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		2514	5	3041	2556	5	3512	2568	1	4224
No Complem.		56	2598	1786	14	2598	1315	2	2602	603
HT2										
Complem.**		2560	51	1802	2566	11	1328	2569	0	616
No Complem.		10	2552	3025	4	2592	3499	1	2603	4211
HT1&HT2										
Complem.***		2508	0	1421	2553	0	1172	2567	0	583
Substit.		5	2551	1399	0	2579	1166	0	2589	567
None		57	52	2007	17	24	2489	3	14	3677
R2 = 10%										
Test	True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
		Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1										
Complem.*		1616	37	1201	2071	24	1649	2495	8	2871
No Complem.		954	2566	3626	499	2579	3178	75	2595	1956
HT2										
Complem.**		2525	976	3661	2547	536	3210	2561	59	1960
No Complem.		45	1627	1166	23	2067	1617	9	2544	2867
HT1&HT2										
Complem.***		1640	34	1125	2085	22	1373	2486	3	1483
Substit.		36	1703	1116	15	2115	1347	3	2539	1485
None		894	866	2586	470	466	2107	81	61	1859

Notes:

Complementarity with one asterisk (Complem.*) is concluded if the test rejects the null of HT1 in testing for complementarity.

Complementarity with two asterisks (Complem.***) is concluded if the test accepts the null of HT2 in testing for complementarity.

Complementarity with three asterisks (Complem.****) is concluded by using one of the following methods: 1) accepting the null hypothesis of HT2 and rejecting the null hypothesis of HT1 in testing the complementarity; 2) rejecting the null of HT1 in the complementarity test and accepting the null of HT1 in the substitutability test; 3) accepting the null of HT2 in the complementarity test and rejecting the null of HT2 in the substitutability test. We have tried these three ways of hypothesis testing in our empirical analysis, exactly the same results are generated.

Table 5. 5 Monte Carlo results of testing pairwise complementarity/substitutability in 3 activities (10,000 repetitions): Sensitivity and Accuracy

R2 = 90%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
TH1									
Sensitivity	99.52%	99.36%		99.76%	99.71%		99.95%	99.95%	
Accuracy	78.27%	77.85%		77.61%	77.07%		76.03%	75.98%	
TH2									
Sensitivity	99.95%	99.84%		99.92%	99.92%		99.92%	99.97%	
Accuracy	96.70%	96.32%		97.72%	97.22%		98.99%	98.98%	
HT1&HT2									
Sensitivity	99.47%	99.23%	77.06%	99.68%	99.52%	83.83%	99.84%	99.89%	92.94%
Accuracy	97.13%	96.65%	93.80%	98.10%	97.57%	95.67%	99.08%	99.06%	98.14%
R2 = 50%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1									
Sensitivity	90.16%	90.05%		95.24%	94.82%		99.17%	98.96%	
Accuracy	82.55%	82.26%		82.28%	81.75%		79.26%	78.89%	
HT2									
Sensitivity	99.52%	99.36%		99.68%	99.63%		99.87%	99.84%	
Accuracy	84.95%	84.68%		89.18%	88.95%		95.30%	95.07%	
HT1&HT2									
Sensitivity	89.81%	89.65%	45.45%	95.29%	95.33%	52.95%	99.06%	98.81%	71.80%
Accuracy	89.44%	89.11%	78.83%	92.52%	92.09%	84.89%	96.28%	95.87%	92.19%
R2 = 10%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1									
Sensitivity	51.18%	48.55%		63.26%	63.74%		89.30%	88.72%	
Accuracy	76.12%	75.01%		79.20%	79.63%		83.16%	82.73%	
HT2									
Sensitivity	97.81%	97.74%		98.29%	98.41%		99.33%	99.36%	
Accuracy	59.66%	60.73%		66.84%	67.19%		83.34%	83.43%	
HT1&HT2									
Sensitivity	50.80%	48.18%	66.63%	63.85%	67.72%	55.60%	89.22%	90.07%	43.24%
Accuracy	76.74%	75.63%	55.15%	80.09%	81.99%	64.42%	88.81%	85.90%	78.38%

Notes:

The sensitivity indicates the proportion of actual complementarities that are correctly identified after 10000 repetitions.

The accuracy is the proportion of correct conclusions (true positives plus true negatives) after 10000 repetitions.

Table 5. 6 Monte Carlo results of testing pairwise complementarity in 4 activities (10,000 repetitions): Sensitivity and Accuracy

R2 = 90%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1									
Sensitivity	99.96%	100.00%		100.00%	99.96%		100.00%	100.00%	
Accuracy	56.57%	56.72%		55.08%	55.18%		53.08%	53.05%	
HT2									
Sensitivity	99.96%	100.00%		99.96%	99.96%		99.96%	100.00%	
Accuracy	94.99%	95.14%		96.51%	96.63%		98.66%	98.65%	
HT1&HT2									
Sensitivity	99.84%	99.58%	80.71%	99.96%	99.62%	86.55%	99.96%	99.42%	94.72%
Accuracy	95.21%	95.33%	90.54%	96.65%	96.75%	93.40%	98.71%	98.58%	97.29%
R2 = 50%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1									
Sensitivity	97.82%	98.04%		99.46%	99.58%		99.92%	100.00%	
Accuracy	68.98%	69.14%		64.69%	64.86%		57.73%	57.88%	
HT2									
Sensitivity	99.61%	99.81%		99.84%	99.81%		99.96%	99.96%	
Accuracy	81.37%	81.53%		86.57%	86.66%		93.83%	93.94%	
HT1&HT2									
Sensitivity	97.59%	98.00%	41.58%	99.34%	99.08%	51.56%	99.88%	99.46%	76.18%
Accuracy	85.17%	85.44%	70.71%	88.11%	88.10%	76.21%	94.14%	94.19%	88.33%
R2 = 10%									
Test \ True	No.Obs = 500			No.Obs = 1000			No.Obs = 5000		
	Complem.	Substit.	None	Complem.	Substit.	None	Complem.	Substit.	None
HT1									
Sensitivity	62.88%	62.50%		80.58%	79.41%		97.08%	97.73%	
Accuracy	78.08%	78.13%		78.28%	78.24%		70.46%	70.65%	
HT2									
Sensitivity	98.25%	98.58%		99.11%	99.08%		99.65%	99.69%	
Accuracy	53.18%	53.83%		62.31%	62.99%		79.72%	79.61%	
HT1&HT2									
Sensitivity	63.81%	65.42%	53.57%	81.13%	81.25%	43.65%	96.73%	97.54%	38.51%
Accuracy	79.11%	79.48%	59.99%	81.20%	81.50%	63.44%	84.30%	84.48%	68.90%

Notes:

The sensitivity indicates the proportion of actual complementarities which are correctly identified as much after 10000 repetitions.

The accuracy is the proportion of correct conclusions (true positives plus true negatives) after 10000 repetitions.

With respect to the accuracy, the increasing of sample size results in higher values of accuracy. However, this positive correlation is only observed for HT1&HT2 and HT2. For HT1, there is rather a negative correlation between accuracy with the sample sizes and the R-square values. The sensitivity declines and the accuracy increases in HT1 when the R-square falls. Increasing the sample size manifests the fluctuation of the accuracy across different R-square values. The same pattern can be observed for both 3 and 4 activities in testing pairwise complementarity/substitutability.

As we discussed in section 5.2.4, the non-exhaustive property of HT1 causes the failure of generating consistent results on complementarity (substitutability) if the vector $R\beta$ contains a negative (positive) value. Table 5.3 and 5.4 decompose the estimated results with respect to the true relationship between two activities. As both Tables shown, HT1 is biased and likely to conclude to complementarity when in fact it belongs to category “None”, especially in situations with R-square values above 0.5. It rejects the null hypothesis to conclude to complementary when there are both negative and positive values in $R\beta$. This bias also explains why the accuracy for HT1 is relatively lower when the R-square is above 0.5. Nevertheless, the bias becomes less severe as the R-square values declines. On the other hand, HT2 gives more accurate results when the model is better specified and with a larger sample size. However, as Table 5.3 shows, the number of false conclusions on complementarity made by HT2 is much higher when the sample size is small and the R-square value is low. So far, we can conclude that HT1 is likely to misjudge “None” as complementarity when the number of observations and the R-square value rise. When the sample size is small and R-square value is low, HT2 tends to conclude to complementarity (accept the null hypothesis) when the true relationship is in fact substitutive and no relationship exists.

The next question is which type of hypothesis test is preferred across different sample sizes and model quality. The findings show that combining HT1&HT2 always gives a better outcome in light of the relatively higher accuracy. Table 5.7 presents the preferable hypothesis between HT1 and HT2 across three different sample sizes and R-square values based on the accuracy.

Table 5. 7 The preferable hypothesis between HT1 and HT2 across different sample sizes and R-square values (conclusions are based on the values of accuracy)

3 STRATEGIES		R-square values		
No. Observations	0.1	0.5	0.9	
500	HT1	HT2	HT2	
1000	HT1	HT2	HT2	
5000	HT1	HT2	HT2	
4 STRATEGIES				
No. Observations	0.1	0.5	0.9	
500	HT1	HT2	HT2	
1000	HT1	HT2	HT2	
5000	HT2	HT2	HT2	

HT1 is preferred when the sample size is small and the R-square value is low. Take the lower left panel of Table 5.6 as an example (the number of observations equals 500 and the R-square equals 10 per cent). For TH1, only 62.88 per cent true complementary relationships are tested corrected⁷⁶ and the accuracy is about 78.08 per cent. For HT2, the accuracy is 53.18 per cent while about 98.25 per cent complementary relationships are judged correctly. Under these circumstances, HT1 is more consistent with the results generated with HT1&HT2 and has a higher accuracy. As shown in Table 5.6, HT1 always performs better when the R-square equals 10 per cent except for the case of 4 strategies and 5000 observations. When the sample size is bigger and the R-square value is higher, HT2 becomes more powerful and accurate. Especially at 90 per cent of the R-square with 5000 observations, HT2 and HT1& HT2 generate nearly equivalent results. As we can see from Table 5.7, HT2 performs in general better than HT1 in testing complementarity/substitutability. HT1 becomes more statistically powerful only when the R-square value is about 0.1.

5.4 Final remarks

By using simulated datasets, this chapter elaborates how to implement the multivariate one-sided tests of complementarity. Two types of hypotheses and their potential problems are discussed. The simulation results verify the potential bias that might exist in the non-exhaustive hypothesis setting. Conclusions based on such hypotheses are likely

⁷⁶ Interpretations are based on the results generated from the LRT.

to be misleading if the nature of the inequalities are not taken into account. The findings also show that HT1 always performs better when the R-square equals 0.1 except for the case of 4 strategies and 5000 observations. When the sample size is bigger and the R-square at a higher level, HT2 becomes more powerful and accurate. Even though combining two tests of hypothesis always guarantees a higher value of accuracy in testing for complementarity, the process of conducting two hypotheses test would cause a loss of efficiency if one does not adjust the level of significance. Our results has shown that, in some situations, only one hypothesis testing can also draw a satisfactory conclusion. For example, with a sample size larger than 5000 and R-square values above 0.9, HT2 is almost equivalent to HT1&HT2.

Chapter 6

Innovation obstacles: evidence from Eastern European and Central Asian countries

6.1 Introduction

In developing countries, most firms engage in innovation by imitating or adapting existing production techniques to local conditions rather than by creating new technologies (Cooper, 1989). Innovation studies in this context have paid particular attention to examining the determinants, sources and capability of innovation and their contributions to firms' performance (Basant and Fikkert, 1996). Few studies, however, investigate which obstacles block innovation or cause innovation failures.

An innovation obstacle is perceived as a factor that potentially prevents an innovation decision or increases the difficulties, timeframe and cost of the process (Hadjimanolis, 2003). Due to inadequate experiences and limited resources, firms in developing countries are more likely to face barriers to innovation. Having a good understanding of the nature of innovation obstacles and their interactive effects is critical for the firm and the government to instigate efficient innovation strategies and policy responses (Hadjimanolis, 2003; Ferriani et al., 2008).

The current chapter helps us to gain a deeper understanding of the innovation obstacles and the potential interplay relationships between them. A firm level dataset - the Investment Climate Survey 2009 (ICS) in Eastern European and Central Asian countries

(EECA) – is used in the empirical analysis. The results reveal the potential obstacles faced by firms and provide policy suggestions on why some obstacles should be removed simultaneously and others should be tackled individually.

The next section outlines the nature of obstacles to innovation and their impact on the innovation decision and output. Section 6.3 specifies the model underlying the empirical analysis. Data and descriptive statistics are introduced in section 6.4. Section 6.5 reports and discusses the empirical findings. Section 6.6 concludes and draws policy suggestions.

6.2 Obstacles in innovation

An obstacle (or barrier) to innovation is defined as any factor that undermines the innovation process (Piatier, 1984). The obstacles faced by firms are perceived differently throughout the innovation process (Hadjimanolis, 2003). Obstacles may represent a major determinant of the decision to abandon ongoing innovation projects or simply delay the innovation outcomes (Baldwin and Hanel, 2003). Even after the firm successfully becomes an innovator, obstacles may emerge and limit the innovation intensity (Mohnen and Röller, 2005).

The potential interactive effects among obstacles are particularly appealing from a policy perspective. For example, if there exists complementarity among obstacles, a policy that focuses only on one obstacle will be assumed to be insufficient. A policy package will be more effective and necessary in this context. Mohnen and Röller (2005) use the Community Innovation Survey (CIS) from four European countries to prove that a policy package is necessary to increase the propensity of becoming innovator due to the identified complementarity, whereas a more individually targeted choice of policies is suggested to eliminate obstacles in order to improve the innovation output for those who are already innovators. Another study regarding the complementarity between innovation obstacles was written by Galia and Legros (2004). The authors investigated innovation obstacles faced by French manufacturing firms by using CIS2 French data. Their findings suggest that there might be interactions and reinforcement among obstacles, and a more targeted choice among policies is expected to improve the innovation performance.

6.3 Model specification

6.3.1 Complementarity between obstacles versus complementarity between policies

Regarding complementarity in obstacles and their corresponding policy responses, two notations need to be clarified: the ‘positive complementarity’ and the ‘negative complementarity’. The former is applied in the situation where the complementary activities are expected to have positive effects on the outcomes. For instance the complementarity between human resource practices and IT infrastructure, product and process innovation or internal and external innovation acquisition sourcing strategies in fostering innovation. The presence of these activities is expected to positively enhance the innovation performance and the complementary effects will be shown as a significantly positive sign of the interaction term. The ‘negative complementarity’ describes an interactive effect between activities that exacerbate the undermining effects to an economic outcome. The sign of the interaction term is expected to be negative. A good example is the complementarity between innovation obstacles. However, if complementarity is strictly interpreted as “the presence of one factor increases the marginal return of the other factor”, which is based on the standard notation given by Milgrom and Roberts (1990a), then complementarity between obstacles indicates a positive interactive effect. The ‘negative complementarity’ would be interpreted as substitutability in this conventional understanding. Differences between these two interpretations are critical for formulating our economic model and interpreting the results. In the current study, we use the second definition: if one obstacle is present and hampers innovation, the second obstacle’s hampering effect is alleviated.

Figure 6.1 geometrically depicts the complementarity between obstacles and also the complementarity between corresponding policies. As the figure shows, the complementarity between two obstacles can be depicted in two different ways, which can accordingly lead to two different interpretations in terms of policy responses. On the one hand, in the presence of both obstacles (-O1 and -O2), if the undermining effect of one obstacle (-O1) reinforces the other obstacle (-O2) by worsening the total effect on the outcome (point D), we define it as ‘negative complementarity’. The policy instruments (O1 and O2) should at least remove one of the obstacles to avoid them appearing together. The complementarity between these two obstacles reflects a substitutive relation between two corresponding policies (point B in figure 6.1). On the other hand,

according to the conventional definition, the complementary relation between -O1 and -O2 can be interpreted as: the presence of one obstacle (-O1) increases the marginal return of the other obstacle (-O2) by mitigating the negative effects (shifting to point E). The complementarity of obstacles then reflects a complementary relationship between two corresponding policies since solving only one obstacle would consequently magnify the deterring effect from the other. The conventional definition of complementarity is adopted in the following analysis.

Figure 6.1 Positive complementary versus negative complementary

6.3.2 Model specification: obstacles in innovation function

Considering there might be other technological acquisition strategies to make firms become innovators, such as acquiring knowledge through licensing, embedded machinery or scientists, we do not exclude firms without R&D investment in our analysis. The Tobit type II model (Heckman-type Selection model or Heckit model, see Amemiya, 1984, 1985) will be employed to measure the intensity of new product sales. It incorporates a selection equation to correct the potential selection bias - firms who are treated may be different from the rest of the observations - caused by the censored data since the innovative sales of new products will only be observed if a firm has achieved

new products or services innovation (Heckman, 1976, 1979; Johnston and DiNardo, 1997; Verbeek, 2000; Greene, 2003; Kleinknecht and Mohnen, 2002; Mohnen and Röller, 2005). Ordinary Least Squares may fail to generate consistent estimates in this case. A dichotomous variable indicating whether a firm has gained new products or services during the period under review is used as the selection indicator. By including obstacles and their interactions in the innovation function, we will be able to systematically examine the potential complementarity.

$$PD_i^o = A + \beta_f Firmspecifics_i + \beta_s Size_i + \beta_c Country_i + \beta_i Industry_i + \varepsilon_i$$

$$PD_i^o = \begin{cases} 0 & \text{if } PD_i^* < 0 \\ PD_i^o & \text{otherwise} \end{cases} \quad (6.1)$$

$$PD_i^* = A + \phi_f Firmspecifics_i + \phi_s Size_i + \phi_c Country_i + \phi_i Industry_i + \eta_i$$

$$PD_i^* = \begin{cases} 1 & \text{if } PD_i^* > 0; \\ 0 & \text{if } PD_i^* \leq 0 \end{cases} \quad (6.2)$$

$$A = \delta_1 x_1 + \delta_2 x_2 + \delta_3 x_3 + \delta_4 x_4 + \delta_{12} x_1 x_2 + \delta_{13} x_1 x_3 + \delta_{14} x_1 x_4 + \delta_{23} x_2 x_3 + \delta_{24} x_2 x_4 + \delta_{34} x_3 x_4 + \delta_{123} x_1 x_2 x_3 + \delta_{124} x_1 x_2 x_4 + \delta_{134} x_1 x_3 x_4 + \delta_{234} x_2 x_3 x_4 + \delta_{1234} x_1 x_2 x_3 x_4 \quad (6.3)$$

where PD_i^o in equation (6.1) indicates the outcome of innovation: sales of new products or services⁷⁷. A is composited of four types of obstacles⁷⁸, $x_l, l = (1, 2, 3, 4)$. “Firmspecifics” captures a vector of firm characteristics that influence firms’ innovation and δ is a vector of estimated coefficients (for detailed explanation of variables, see next section). Size, Country and Industry are three sets of dummies to control for size, location and industry specificities of firm i . ε_i denotes the disturbance term.

Equation (6.2) specifies the selection equation. PD_i^* is the latent value of the selection for firm i in (6.2). It tells whether a firm produces any new products or services during the period under review. We observe the outcome PD_i^o only if the latent selection

⁷⁷ Due to the fact that R&D is not the only technological sourcing to innovation, other sourcing channels such as technology licensing, embedded machinery and imitation (these information are not available from the current data source) may also present and contribute to innovation output, R&D will not be used as indicator for the selection equation in the Heckman model. Based on the data in the empirical part, there are about 36.55% of firms which claims to be product innovators without R&D investment.

⁷⁸ In equation 6.3, subscript i has been deleted to ease the writing.

variable PD_i^* is non-negative. It is assumed that the error term η_i and ε_i follow a joint normal distribution (Heckman, 1979; Greene, 2003). Variables in (6.2) are defined the same as in equation (6.1) except *firmspecifics*_{*i*} that should contain at least one extra exogenous variable as instrument in the selection equation, in order to avoid the identification problem (Greene, 2003; Toomet and Henningsen, 2008).

6.3.3 Testing complementarity between pairs of obstacles

Turning to the obstacles, $x_l, l = (1, 2, 3, 4)$ in (6.3) are dichotomous choice variables which correspond to four types of obstacles in regard to innovation performance. x_l equals to one if the corresponding obstacle is reported as a major obstacle by the firm, otherwise zero. δ is a vector of coefficients that need to be estimated. Obstacles here are treated as exogenous variables that do not correlated with the residual. According to the notion of complementarity (Milgrom, 1990b; 1995), we conclude obstacle x_i and x_j are complementary if the following condition is satisfied.

$$f(x_i = 1, x_j = 1 | Z) + f(x_i = 0, x_j = 0 | Z) \geq f(x_i = 1, x_j = 0 | Z) + f(x_i = 0, x_j = 1 | Z) \quad (6.4)$$

In the case of more than two obstacles, testing the complementarity between pairs of obstacles should include the full set of cross-terms in (6.3). For example, the complementarity between x_1 and x_2 can only be concluded if all of the following inequalities are satisfied and with at least one inequality holding strictly (for details, see chapter 5.3).

$$\left\{ \begin{array}{l} f_{1,2}(x_1, x_2 | x_3 = 0, x_4 = 0) = \delta_{12} \geq 0 \\ f_{1,2}(x_1, x_2 | x_3 = 1, x_4 = 0) = \delta_{12} + \delta_{123} \geq 0 \\ f_{1,2}(x_1, x_2 | x_3 = 0, x_4 = 1) = \delta_{12} + \delta_{124} \geq 0 \\ f_{1,2}(x_1, x_2 | x_3 = 1, x_4 = 1) = \delta_{12} + \delta_{123} + \delta_{124} + \delta_{1234} \geq 0 \end{array} \right. \quad (6.5)$$

If all inequalities have the inverse sign in (6.5), then we have a substitutability⁷⁹. The same formula can be adopted for testing pairwise complementarity for x_1 and x_3 ; x_1 and x_4 ; x_2 and x_3 ; x_2 and x_4 ; x_3 and x_4 . In the case of more than two obstacles, estimation without controlling for the full cross-terms (the third- and fourth-order interactions) is

⁷⁹ Previous studies of Athey and Stern (1998) and Mohnen and Röller (2005) refer x_1 and x_2 as “strictly complementary” if the “ $\geq$ ” is replaced by “ $>$ ”.

inconclusive. Specifically, only looking at δ_{12} by ignoring the third and the fourth-order interactions in (6.3) may lead to a biased conclusion (Mohnen and Röller, 2005; Lokshin et al., 2007; Carree et al., 2011). With multiple inequality restrictions imposed on δ , the one-sided multivariate hypotheses used for testing complementarity are

$$\text{Hypothesis Test 1} \quad H_0 : R\delta = 0 \quad \text{vs} \quad H_1 : R\delta \geq 0 \quad (6.7)$$

$$\text{Hypothesis Test 2} \quad H_0 : R\delta \geq 0 \quad \text{vs} \quad H_1 : R\delta \not\geq 0 \quad (6.8)$$

R is a matrix with a dimension of $(p \times k)$ which defines the inequality restrictions imposed on the estimated parameters. p is the number of inequality constraints that have to be tested simultaneously. HT1 (Hypothesis Test 1) tests equality against at least one inequality strictly holding. HT2 (Hypothesis Test 2) tests if all $R\delta$ are larger or equal to zero against at least one violation in the null hypothesis (not all $R\delta$ are larger or equal to zero)⁸⁰. “!” sign denotes “not”. We emphasize a test procedure that takes into account both HT1 and HT2 herein, which have better statistical power than the test procedures that only consider one of them. A likelihood ratio test (Gourieroux, 1982) is used as the hypothesis testing method. In our empirical analysis, the testing reference for a multivariate distribution is derived by the method discussed in chapter 5⁸¹.

6.4 Data and variables

6.4.1 Data

The firm-level data Investment Climate Survey (ICS)⁸² conducted by World Bank covers a broad range of topics including infrastructure, economic performance and investment environment.

⁸⁰ HT1 is not defined to be exhaustive. The null hypothesis of HT1 is equality only. See more details in chapter 5.2.4.

⁸¹ For details with respect to the test statistics, please see chapter 5. The empirical estimation was done by using statistical program R. The programming code is available upon request.

⁸² Enterprise Surveys (<http://www.enterprisesurveys.org>), The World Bank.

Table 6. 1 Variables definition and summary (mean and SD)

Variable		Mean	Std. Dev.	Min	Max	obs.
Fin_obs	Binary variable equals to 1 if "Access to finance" is recognized as a major or serious obstacle in a firm	0.29	0.45	0	1	7712
Lab_obs	Binary variable equals to 1 if "Inadequately educated workforce" is recognized as a major or serious obstacle in a firm	0.34	0.47	0	1	7712
Com_obs	Binary variable equals to 1 if "Practices of competitors in the informal sector" is recognized as a major or serious obstacle in a firm	0.29	0.46	0	1	7712
Tax_obs	Binary variable equals to 1 if "Tax rates: is recognized as a major or serious obstacle in a firm	0.47	0.50	0	1	7712
Prodsales	Per cent of annual sales accounted for by new products or services in 2007, in percentage	0.28	0.25	0.0001	0.99	4508
PROD	In the last three years, has this establishment introduced new products or services?	0.58	0.49	0	1	7712
RnDdum	Did this establishment spend on research and development activities, either in-house or contracted with other companies (outsourced)?	0.27	0.44	0	1	7712
Discont	In the last three years, has this establishment discontinued at least one product line or service?	0.26	0.44	0	1	7712
Upgrade	In the last three years, has this establishment upgraded an existing product line or service?	0.80	0.40	0	1	7712
lnsale2007	Turn over of 2007, in logarithm (USD)	6.79	2.25	-0.568	18.197	7712
Sizedum2	Binary variable equals to 1 if total employees of a firm > 25 and < 100	0.29	0.46	0	1	7712
Sizedum3	Binary variable equals to 1 if total employees of a firm > 100	0.24	0.43	0	1	7712
Expercent	Export as percentage in total sales of 2007, in percentage	11.75	26.41	0	100	7712
Forown	Percentage of foreign ownership of firm, in percentage	7.24	23.84	0	100	7712
ISO	Does this establishment have an internationally recognized quality certification? Some examples are: ISO 9000, 9002 or 14000.	0.26	0.44	0	1	7712
Age	Age of the firm by the end of 2007	17.19	16.37	1	184	7712
Subsidy	Over the last three years has this establishment received any subsidies from the national, regional or local governments or European Union sources?	0.10	0.30	0	1	7712
Regu_time	Senior management's time spent on dealing with regulations	13.39	19.82	0	100	7712
Hi-tech	Binary variable equals to 1 if a firm belongs to High technology industry according to OECD High-Technology industry classification.	0.08	0.27	0	1	7712

Table 6. 2 Mean values of variables across countries

Country	Income	Freq.	RnD dum	PRO D	Ln_ Sale 2007	Ln_ size	Ex_ perce nt	For_ own	ISO	Age	Subsi dy	Regu time	Hi- tech
Albania	Upper-Middle	84	0.25	0.27	6.61	2.99	11.00	16.13	0.21	11.82	0.01	16.42	0.02
Belarus	Upper-Middle	187	0.22	0.70	6.80	3.75	8.58	6.22	0.12	18.22	0.05	17.30	0.05
Georgia	Low/Lower-Middle	205	0.15	0.35	5.49	3.26	6.98	3.34	0.16	11.55	0.04	1.92	0.01
Tajikistan	Low/Lower-Middle	249	0.12	0.51	4.55	3.16	3.60	4.69	0.14	15.74	0.04	13.29	0.06
Turkey	Upper-Middle	736	0.30	0.51	8.42	3.84	25.52	2.19	0.47	18.97	0.10	27.47	0.14
Ukraine	Low/Lower-Middle	492	0.20	0.60	5.93	3.52	9.84	5.89	0.12	18.18	0.03	11.74	0.22
Uzbekistan	Low/Lower-Middle	264	0.03	0.29	5.35	3.60	3.91	9.25	0.09	20.81	0.03	16.52	0.08
Russia	Upper-Middle	680	0.39	0.71	7.73	4.18	4.41	3.85	0.20	19.24	0.08	19.28	0.24
Poland	High	211	0.27	0.63	7.65	3.42	12.97	7.60	0.27	20.08	0.18	12.83	0.04
Romania	Upper-Middle	263	0.26	0.51	7.31	3.74	9.90	12.00	0.43	14.59	0.13	11.67	0.04
Serbia	Upper-Middle	310	0.36	0.67	7.64	3.74	10.69	10.07	0.28	25.90	0.08	15.33	0.07
Kazakhstan	Upper-Middle	359	0.13	0.49	6.76	3.71	1.58	3.44	0.17	10.51	0.04	5.84	0.05
Moldova	Low/Lower-Middle	284	0.31	0.54	6.13	3.54	10.74	7.81	0.12	12.88	0.07	9.53	0.01
Bosnia and Herze	Upper-Middle	238	0.51	0.64	7.53	3.54	17.06	5.55	0.35	22.78	0.17	12.74	0.04
Azerbaijan	Upper-Middle	262	0.08	0.51	5.72	3.08	2.37	7.94	0.16	16.99	0.05	3.44	0.03
Fyr	Low/Lower-Middle	253	0.42	0.64	6.92	3.45	23.85	8.40	0.25	17.80	0.05	15.10	0.03
Macedonia	Low/Lower-Middle	224	0.22	0.64	5.80	2.97	6.64	5.82	0.23	11.84	0.01	11.33	0.06
Armenia	Low/Lower-Middle	158	0.16	0.48	5.18	3.33	8.84	10.66	0.18	16.94	0.09	5.51	0.05
Kyrgyz Republic	Low/Lower-Middle	330	0.24	0.72	5.59	3.36	6.07	4.83	0.16	14.69	0.09	12.75	0.02
Mongolia	Low/Lower-Middle	203	0.37	0.70	7.87	3.64	18.21	15.39	0.29	17.01	0.22	6.89	0.04
Estonia	High	166	0.29	0.59	5.67	2.60	4.46	0.00	0.14	14.82	0.02	9.77	0.01
Kosovo	Low/Lower-Middle	146	0.34	0.64	7.94	3.50	18.12	10.34	0.51	13.82	0.29	12.36	0.09
Czech Republic	High	254	0.17	0.43	8.32	3.79	12.39	14.93	0.52	15.07	0.19	16.06	0.05
Hungary	High	207	0.18	0.59	7.75	3.67	16.22	14.83	0.27	14.04	0.14	9.42	0.01
Latvia	Upper-Middle	215	0.23	0.72	7.30	3.47	18.93	8.16	0.20	13.43	0.17	11.21	0.04
Lithuania	Upper-Middle	150	0.19	0.59	7.66	3.55	14.74	9.51	0.41	14.92	0.15	7.89	0.05
Slovak Republic	High	240	0.43	0.76	3.13	3.68	24.72	10.80	0.43	24.62	0.25	9.13	0.06
Slovenia	High	161	0.40	0.55	6.90	3.33	12.24	10.88	0.29	15.93	0.03	12.00	0.04
Bulgaria	Upper-Middle	116	0.55	0.74	8.39	3.80	17.49	8.59	0.29	26.60	0.34	14.79	0.06
Croatia	High	65	0.32	0.75	7.50	3.20	7.02	6.91	0.25	14.28	0.03	8.00	0.02
Montenegro	Upper-Middle												
Total		7,712	0.27	0.58	6.79	3.57	11.75	7.24	0.26	17.19	0.10	13.39	0.08

In this chapter, we use the data from Eastern Europe and Central Asia 2008 (EECA 2008) because it is based on the same questionnaire across 31 countries in this region,

yielding comparable information on innovation and firm-specific variables. It collects information on whether a firm recently had new product or services innovation, R&D activities, and the strength of different sets of obstacles to firm's production and performance. Table 6.1 defines variables and presents the summary statistics. After cleaning the missing values⁸³, our final sample includes 7,712 firms and distributes across a wide range of manufacturing and service industries in 31 countries. Table 6.2 summarizes the variables by country.

6.4.2 Measures for innovation performance

The dependent variable of the selection equation (6.2) is measured by a dichotomous variable PD, which takes the value 1 if a firm introduced new products or services during the period under review⁸⁴. Innovation performance (the dependent variable of equation (6.1)) is measured by the percentage of new products and services sales in total turnover. This share-in-sales indicator is the direct link between the innovation effort and the commercial success and has been widely used as output indicator in recent years (Klomp and Van Leeuwen, 1999; Mairesse and Mohnen, 2001). Dichotomous choice variable RnD equals to 1 if a firm has invested in R&D during the period under review. Table 6.3 describes the R&D and innovativeness across firms in different sectors, income levels⁸⁵ and size groups⁸⁶.

As shown in Table 6.3, firms in manufacturing, higher-income and larger-sized groups are more likely to succeed in innovation. In view of the new product sales, manufacturing firms have a higher value compared with firms in the service sector, 29 per cent and 26 per cent. However, the lower-income and smaller-sized firms tend to be higher in proportion of commercialized innovation in the total turnover. In total, 58 per cent of the sampled firms engage in product innovation and the average level of innovation sales is about 0.28 per cent. It is important to note that the product

⁸³ First, firms with fewer than 5 employees are deleted (3.6%) from our sample. Second, firms that do not aim at innovating are also filtered out from sample (D'Este et al., 2008, Savignac, 2008). Specifically, firms that are not aiming at innovating do not carry out innovation activities at all. So they do not observe the potential obstacles to innovation. Last, we assume that non-innovative firms which experienced unsuccessful innovation would encounter at least one of the obstacles. Therefore, we drop firms which have not had any new or updated products/services and, at the same time, report that none of the obstacles is important. It accounts for 6.2% of the total sample.

⁸⁴ Process innovation related measurements are not covered by the current questionnaire, so the influence of obstacles to process innovation will not be studied here.

⁸⁵ The income-group definition and classification is based on the World Bank country classification. For detail definition, please see: <http://data.worldbank.org/about/country-classifications>.

⁸⁶ As shown in table 6.3, there are about 76 per cent of firms with a size of smaller than 100 employees. The total sample is divided into three groups according to the distribution of the size of firms: 5-25 (47% of total sample), 26-100 (29% of total sample) and above 100 (24% of total sample).

innovation in developing countries may be new products or services which are only new to the firm itself, not necessarily new to the market.

Table 6. 3 R&D and innovation output status of all and across each group (mean values)

	RnDdum	Prodinno	Prodsales	Logit-prod	Freq.	Percentage
Sector						
Service	0.22	0.58	0.26	-1.35	3,414	44.27
Manufacturing	0.31	0.59	0.29	-1.19	4,298	55.73
Income						
Low and lower-middle	0.22	0.55	0.29	-1.18	2,625	34.04
Upper-middle	0.29	0.59	0.28	-1.22	3,767	48.85
High	0.32	0.63	0.24	-1.52	1,320	17.12
Size						
5<x<25	0.19	0.54	0.29	-1.15	3,595	46.62
26<x<100	0.29	0.60	0.28	-1.25	2,263	29.34
>100	0.40	0.64	0.25	-1.46	1,854	24.04
Total	0.27	0.58	0.28	-1.26	7712	100

6.4.3 Obstacle measures

Definition: Obstacles in ICS and Obstacles in CIS

There are in total fifteen different obstacles investigated in the ICS-EECA2008. All respondents were asked how intensely each obstacle has affected their firm during the period under review. We have chosen four most important barriers based on the question: which is the biggest obstacle faced by firm? (see Appendix 6A). They are obstacles in the category of finance, skilled labor, informal competition and tax respectively. Four dichotomous variables are constructed to indicate whether the firm assesses each as a major impediment. Questions are asked about obstacles to innovation on a four-point Likert scale. The corresponding obstacle variable takes the value 1 if the answer is marked as a major or very severe obstacle (scores 3 and 4), and takes the value zero otherwise.

The obstacles defined in the ICS are impediments faced by a firm in their entire operation process, which is different from the obstacles defined in the Community

Innovation Survey (CIS). The CIS addresses obstacles as the barriers faced by firms particularly to their innovation. The obstacles in ICS are characterized by having a broad range and various categories. We expect that obstacles to a firm's operation will also undermine its innovation performance, especially when a firm intends to become an innovator⁸⁷.

Classification: Internal and external obstacles

Obstacles can be classified in different ways. The most common one is to differentiate between obstacles internal and external to the firm (Piatier, 1984; Hadjimanolis, 2003). Internal obstacles refer to factors that are generated internally and related to the organization characteristics, employees' quality and the management structure. External obstacles are related to supply, demand and the environment (Hadjimanolis, 1999), for example, difficulties in acquiring external technological information, incorrect perception of target market, and government regulations.

Difficulty in securing finance is recognized as one of the most severe internal barriers to innovation. Financial constraints as internal hampering factors to innovation have been extensively dealt with in previous literature. Himmelberg and Petersen (1994) use small firms in the high-tech industries to show a significant positive relationship between internal finance and firms' R&D. Stockdale (2002) reports that financial constraints are the second most important impeding factor for innovation for active firms in UK, after the high innovation costs. Similar results also have been obtained by other studies (e.g. Mulkay, Hall and Mairesse, 2001; Savignac, 2006; Tiwari et al., 2008).

Lack of skilled labor is another major internal obstacle that hampers innovation (Hadjimanolis, 1999). Innovation cannot be achieved without efficient utilization of R&D by qualified human capital. Skilled labor is also required in the production process to absorb and transfer ideas into new products. The concept of "absorptive capacity" proposed by Cohen and Levinthal (1990) also suggests that high levels of skills are necessary within a firm in order to appropriate external knowledge.

Considered as an external obstacle, competition from the informal sector is ranked as one of the biggest obstacles by firms in our sample (10.76 per cent). Informal competition may damage innovation since the cost advantage informal firms enjoy is a

⁸⁷ By filtering out firms that do not intend to become an innovator (see footnote 77), it helps us to rule out the potential non-innovation related obstacles that are perceived by firms.

result of ignoring regulations (e.g. intellectual property regulations). While regulation is a major determinant of the intensity of competition from the informal sector, severe obstacles caused by competition from the informal sector may indicate the poor regulatory and institutional quality that prevails in the market. Estimates by Schneider (2005) over 145 countries across the globe show that informality is an issue correlated with low-income countries.

Corporate taxation may influence firms' investment decisions and profits. Classified as another external obstacle, the tax rate has been ranked as the biggest obstacle to firms' production in EECA countries in 2008. High corporate taxes may reduce incentives for innovations by reducing their post-tax returns. Hence, a negative effect of corporate taxes on firm level innovation is expected (Arrow, 1962). The issue of taxation and innovation is complex in the sense that innovative activity of firms is associated with many aspects and levels of taxation. Favorable taxation regimes are expected to create additional and important incentives for innovation (Mohnen, 2000).

Savignac (2008) suggests that a positive correlation between the obstacles and innovation performance might be raised by firms that are not willing to innovate. Hence, it is important to distinguish between firms which opted not to become innovators and those who could not because of obstacle standing in their way. We try to filter out the former by excluding firms that do not aim at innovation and, at the same time, perceive no obstacles in their production and innovation process (Savignac, 2008)⁸⁸.

Table 6.4 shows the percentage of the presence of obstacles across different innovativeness. Generally, innovation active and product innovation oriented firms are more likely to be burdened by competition from the informal sector and by tax rates, while non-innovation active and non-product innovating firms tend to be hampered more by inadequate finance and skilled labor.

⁸⁸ This is done in order to correct for a sample selection problem (Mohnen and Röller, 2005; Savignac, 2008). In particular, the survey includes two questions asking whether the firm has achieved new products/service innovation and upgraded their products/services during the period under review. If a firm responds negatively to these two questions, we classified him as non-potential products innovator. The underlying rationale is that non-innovating firms that did not experience any obstacle to innovation are unlikely to have the intention to innovate.

Table 6. 4 Obstacles in innovators and non-innovators (mean values and percentages)

	Fin_obs	Lab_obs	Com_obs	Tax_obs	Freq.	Percent
R&D investor						
No	0.28	0.33	0.29	0.48	5,634	73.05
Yes	0.30	0.37	0.29	0.44	2,078	26.95
New products or services						
No	0.27	0.31	0.30	0.49	3,204	41.55
Yes	0.30	0.37	0.29	0.45	4,508	58.45
Total	0.29	0.34	0.29	0.47	7712	100

6.4.4 Patterns of obstacles

Sector. The sector in which a firm operates may influence the barriers it faces because different sectors are characterized by the nature of their products, market structure and legislation (Preissl, 1990). Hadjimanolis (2003) suggests that firms in different sectors perceive barriers to innovation differently. In EECA countries, firms in the manufacturing sector are in general more active in innovation. As shown in Table 6.5, 31 per cent of the manufacturing firms invest in R&D, compared with 22 per cent in the service sector. It also shows that obstacles appear more frequent in the manufacturing sector except for the informal competition. This might be due to the fact that manufacturing firms start recognizing the obstacles through innovation. Service firms are more likely to struggle with informal competition since more than 30 per cent report it as a major obstacle while the financial barrier is more serious for manufacturing firms.

Income level. Firms from less developed countries have to face more severe constraints in innovation due to their relatively weak infrastructure, inadequate resources and government supports (Hadjimaonolis, 1999). Table 6.5 suggests that fewer firms from high-income countries encounter obstacles during their production compared with firms from the low and low-middle income groups. The low and low-middle income groups are pressured by inadequate finance and more than 17 per cent of the firms rate it as a severe obstacle, which is about 5 and 17 percentage points higher compared with upper-middle income and high-income groups. The informal competition also seems to seriously hamper firms' production and innovation in low and middle-income countries. The labor and tax related obstacles more often appear in firms from upper-middle countries. Half of the firms from upper-middle income countries perceive high tax rates

as a major obstacle and the percentages are 44 per cent and 41 per cent respectively for low-income and high-income group.

Firm size. Piatier (1984) explained that the patterns of obstacles faced by firms differ greatly associating with their size as well. Small firms generally perceive impediments as more severe (Hadjimanolis, 2003). Statistics in Table 6.5 exhibit that bigger size firms (the number of employees above 100) are less likely to encounter obstacles except for the lack of skilled labor. Informal competition seems to severely constrain small firms (with number of employees between 5 and 25). Firms with employees between 26 and 100 have the highest frequency of reporting the tax rate as an obstacle, 49 per cent.

Table 6. 5 Obstacles across different sector, income and size groups (mean values and percentages)

	Fin_obs	Lab_obs	Com_obs	Tax_obs	Freq.	Percent
Sector						
Service	0.27	0.31	0.30	0.44	3,414	44.27
Manufacturing	0.30	0.36	0.29	0.49	4,298	55.73
Income						
Low and lower-middle	0.34	0.34	0.36	0.44	2,625	34.04
Upper-middle	0.29	0.38	0.28	0.50	3,767	48.85
High	0.17	0.24	0.19	0.41	1,320	17.12
Size						
5<x<25	0.29	0.30	0.32	0.45	3,595	46.62
26<x<100	0.29	0.36	0.30	0.49	2,263	29.34
>100	0.28	0.39	0.23	0.47	1,854	24.04
Total	0.29	0.34	0.29	0.47	7712	100

6.4.5 Firm specificities

A set of control variables that captures the firm characteristics will be included in the innovation equation. Sales_log is the logarithm of total turnover in 2002 (in USD). It denotes the scale of the firm. Firms with a higher turnover are expected to have more financial resources to allocate to innovation. Age indicates the number of years a firm has been operating since it started. On the one hand, Age is expected to adversely affect innovation outcome (Tushman and Anderson, 1986; Henderson, 1993; Katrak, 1997) because younger firms are more creative and entrepreneurial dynamic. On the other

hand, longer operation experience gives a firm prior expertise, already-established financial resources and other complementary assets. Accordingly, older firms are more likely to tackle obstacles that stand in their way (Schoonhoven et al., 1990; Tripsas, 1997). *Ex_percent* indicates the share of export (indirect and direct) in the total turnover during the period under review. Exporting firms face fiercer competition on the international market. It stimulates firms to be more innovative. However, in the case of EECA countries, firms might compete in the international market with a price advantage of already-existing products due to cheap material and labor. This might inhibit innovation, especially innovation in new products. Therefore, the sign of *Ex_percent* here is ambiguous. *For_percent* indicates the percentage of foreign ownership. Foreign owned firms are characterized by higher capital intensity, high quality of human capital and efficient management. Many previous studies suggest that foreign owned firms are more productive (Globerman et al., 1994; Doms and Jensen, 1998; Kimura and Kiyota, 2007). However, it is also argued that foreign owned firms tend to concentrate their R&D in their home countries (OECD, 2003).

Regu_time records the percentage of time the senior manager spends in dealing with government regulations. It measures how burdensome it is for firms to comply with government regulations. On the one hand, each hour spent in dealing with government regulations is an hour not devoted to making the business more productive. A higher burden of regulations causes less willingness to expand production and innovation. On the other hand, the more time a manager spends also indicates a better understanding of government regulation and consequently benefits both internal (in-house R&D) and external (co-operative innovation or licensing) innovative activities.

Table 6. 6 Generalized Tobit estimation results: full sample and across different sectors

Dependent variable: New products sales	Full Sample		Sectors			
			Manufacturing		Services	
	Outcome	Selection	Outcome	Selection	Outcome	Selection
Fin_obs	0.242 (0.153)	-0.296*** (0.074)	0.353* (0.203)	-0.295*** (0.098)	0.010 (0.238)	-0.303*** (0.114)
Lab_obs	0.092 (0.117)	-0.158** (0.063)	0.228 (0.171)	-0.255*** (0.085)	-0.030 (0.167)	-0.037 (0.097)
Com_obs	0.075 (0.145)	-0.281*** (0.068)	0.372* (0.214)	-0.288*** (0.100)	-0.264 (0.201)	-0.286*** (0.095)
Tax_obs	0.172 (0.128)	-0.350*** (0.052)	0.183 (0.168)	-0.342*** (0.071)	0.037 (0.197)	-0.363*** (0.078)
Fin_Lab	-0.082 (0.255)	0.476*** (0.135)	-0.437 (0.357)	0.631*** (0.185)	0.387 (0.372)	0.304 (0.202)
Fin_Com	-0.322 (0.283)	0.410*** (0.141)	-0.823** (0.398)	0.384* (0.200)	0.304 (0.417)	0.469** (0.203)
Fin_Tax	-0.390* (0.230)	0.449*** (0.109)	-0.483 (0.298)	0.365** (0.146)	-0.061 (0.375)	0.585*** (0.167)
Lab_Com	-0.342 (0.255)	0.458*** (0.128)	-0.898** (0.373)	0.658*** (0.178)	0.297 (0.352)	0.203 (0.186)
Lab_Tax	-0.223 (0.194)	0.346*** (0.097)	-0.283 (0.260)	0.328** (0.128)	-0.075 (0.292)	0.338** (0.150)
Com_Tax	-0.035 (0.214)	0.316*** (0.102)	-0.132 (0.297)	0.206 (0.143)	0.188 (0.324)	0.441*** (0.150)
Fin_Lab_Com	0.593 (0.447)	-0.494** (0.245)	1.393** (0.614)	-0.554 (0.342)	-0.474 (0.675)	-0.458 (0.359)
Fin_Lab_Tax	-0.084 (0.333)	-0.367** (0.184)	0.072 (0.444)	-0.326 (0.248)	-0.356 (0.520)	-0.438 (0.280)
Fin_Com_Tax	0.425 (0.390)	-0.519*** (0.195)	0.787 (0.525)	-0.264 (0.269)	-0.294 (0.635)	-0.917*** (0.288)
Lab_Com_Tax	0.317 (0.335)	-0.286 (0.179)	0.709 (0.459)	-0.256 (0.244)	-0.303 (0.510)	-0.316 (0.271)
Fin_Lab_Com_Tax	-0.602 (0.568)	0.449 (0.314)	-1.178 (0.761)	0.024 (0.430)	0.587 (0.934)	1.097** (0.474)
Lnsale2007	-0.024 (0.029)	0.083*** (0.012)	-0.047 (0.037)	0.064*** (0.017)	0.038 (0.048)	0.104*** (0.017)
Expercent	0.003** (0.001)	-0.002*** (0.001)	0.003** (0.002)	-0.002** (0.001)	0.001 (0.002)	-0.001 (0.001)
Forown	0.001 (0.001)	0.002** (0.001)	0.001 (0.002)	0.000 (0.001)	0.004* (0.002)	0.003*** (0.001)
ISO		0.103** (0.041)		0.111** (0.052)		0.118* (0.068)
RnDdum	0.200 (0.182)	0.787*** (0.040)	0.070 (0.250)	0.862*** (0.051)	0.506** (0.238)	0.683*** (0.064)
Age	-0.010*** (0.002)	-0.001 (0.001)	-0.008*** (0.002)	-0.000 (0.001)	-0.015*** (0.004)	-0.002 (0.002)
Subsidy		0.240*** (0.057)		0.228*** (0.072)		0.256*** (0.096)
Regu_time1	0.005*** (0.002)	-0.000 (0.001)	0.006*** (0.002)	-0.001 (0.001)	0.006** (0.003)	0.001 (0.001)
Hitech	-0.098 (0.364)	-0.053 (0.253)	0.346 (0.378)	0.888*** (0.172)		
Sizedum2	-0.100 (0.076)	-0.024 (0.042)	-0.016 (0.106)	-0.031 (0.057)	-0.168 (0.114)	-0.036 (0.063)
Sizedum3	-0.198* (0.108)	-0.159*** (0.057)	-0.082 (0.155)	-0.199** (0.079)	-0.313** (0.155)	-0.074 (0.087)
Constant	-0.267 (0.498)	0.302 (0.272)	-0.705 (0.790)	-0.513* (0.306)	-0.791 (0.682)	0.137 (0.322)
Observations	7,712	4,508	4,298	2,537	3,414	1,971

Standard errors in parentheses

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

Table 6. 7 Generalized Tobit estimation results: across different income levels

Dependent variable: New products sales	Income pattern					
	Low and Low-middle		Upper-middle		High	
	Outcome	Selection	Outcome	Selection	Outcome	Selection
Fin_obs	0.550** (0.259)	-0.249** (0.118)	0.242 (0.234)	-0.352*** (0.110)	-0.296 (0.329)	-0.173 (0.203)
Lab_obs	0.161 (0.229)	-0.135 (0.113)	0.076 (0.173)	-0.173* (0.092)	0.085 (0.232)	-0.212 (0.146)
Com_obs	0.500* (0.272)	-0.344*** (0.108)	-0.165 (0.218)	-0.303*** (0.101)	0.209 (0.304)	-0.036 (0.200)
Tax_obs	0.500 (0.321)	-0.526*** (0.099)	0.174 (0.171)	-0.299*** (0.075)	-0.025 (0.209)	-0.270** (0.115)
Fin_Lab	-0.318 (0.449)	0.156 (0.223)	-0.234 (0.385)	0.721*** (0.193)	1.365** (0.611)	0.473 (0.420)
Fin_Com	-0.713 (0.459)	0.344 (0.213)	0.042 (0.438)	0.533** (0.211)	-1.310* (0.759)	0.182 (0.475)
Fin_Tax	-0.713 (0.440)	0.468** (0.184)	-0.517 (0.328)	0.430*** (0.158)	0.298 (0.507)	0.664** (0.306)
Lab_Com	-0.768 (0.485)	0.592*** (0.209)	-0.232 (0.374)	0.503*** (0.182)	-0.135 (0.670)	-0.208 (0.407)
Lab_Tax	-0.290 (0.448)	0.515*** (0.184)	-0.337 (0.261)	0.288** (0.132)	-0.008 (0.413)	0.421* (0.249)
Com_Tax	-0.504 (0.453)	0.564*** (0.174)	0.048 (0.312)	0.202 (0.149)	-0.046 (0.441)	0.180 (0.269)
Fin_Lab_Com	1.195 (0.733)	-0.257 (0.372)	0.240 (0.679)	-0.769** (0.366)	-1.255 (1.628)	-0.402 (0.900)
Fin_Lab_Tax	-0.218 (0.640)	-0.093 (0.319)	0.345 (0.468)	-0.495* (0.255)	-1.938** (0.906)	-1.133** (0.572)
Fin_Com_Tax	0.591 (0.674)	-0.522* (0.306)	0.529 (0.574)	-0.420 (0.290)	1.263 (1.032)	-0.954 (0.603)
Lab_Com_Tax	0.366 (0.670)	-0.592* (0.309)	0.677 (0.481)	-0.232 (0.251)	-0.817 (0.879)	0.301 (0.536)
Fin_Lab_Com_Tax	-0.547 (0.991)	0.355 (0.501)	-1.056 (0.826)	0.388 (0.459)	1.779 (1.946)	1.454 (1.097)
Ln sale2007	-0.087 (0.060)	0.098*** (0.019)	0.003 (0.040)	0.081*** (0.018)	-0.109* (0.058)	0.056* (0.033)
Expercent	-0.000 (0.002)	-0.000 (0.001)	0.003 (0.002)	-0.003*** (0.001)	0.005** (0.003)	-0.002 (0.002)
Forown	0.002 (0.002)	-0.001 (0.001)	0.001 (0.002)	0.002 (0.001)	0.001 (0.002)	0.005*** (0.002)
ISO		0.133* (0.081)		0.091 (0.056)		0.146 (0.099)
RnDdum	-0.077 (0.348)	0.817*** (0.074)	0.299 (0.247)	0.809*** (0.055)	-0.157 (0.281)	0.744*** (0.098)
Age	-0.009** (0.004)	0.000 (0.002)	-0.012*** (0.003)	-0.003** (0.001)	-0.007** (0.004)	-0.000 (0.003)
Subsidy		0.162 (0.131)		0.311*** (0.084)		0.225** (0.104)
Regu_time1	0.005 (0.004)	-0.004*** (0.002)	0.006*** (0.002)	0.001 (0.001)	0.010** (0.004)	0.003 (0.003)
Hitech	-0.322 (0.926)	0.333 (0.457)	-0.104 (0.587)	-0.832* (0.476)	0.030 (0.580)	0.549 (0.529)
Ln sale2007	-0.108 (0.140)	0.005 (0.071)	-0.077 (0.109)	-0.028 (0.060)	-0.059 (0.178)	-0.111 (0.110)
Sizedum2	-0.181 (0.232)	-0.245** (0.102)	-0.149 (0.153)	-0.138* (0.082)	-0.072 (0.231)	-0.108 (0.148)
Sizedum3	-0.340 (1.176)	-0.554 (0.366)	-0.584 (0.612)	0.920** (0.465)	0.338 (0.746)	0.288 (0.434)
Constant						
Observations	2625	1,442	3,670	2,233	1,320	8,33

Standard errors in parentheses

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

Table 6. 8 Generalized Tobit estimation results: across different size groups

Dependent variable: New products sales	Size pattern					
	Small (5-25)		Medium (26-100)		Large (> 100)	
	Outcome	Selection	Outcome	Selection	Outcome	Selection
Fin_obs	0.010 (0.208)	-0.264** (0.104)	0.278 (0.286)	-0.187 (0.147)	0.468 (0.329)	-0.397** (0.161)
Lab_obs	-0.030 (0.200)	-0.293*** (0.096)	-0.010 (0.222)	-0.036 (0.121)	0.308 (0.202)	-0.008 (0.128)
Com_obs	0.195 (0.237)	-0.426*** (0.092)	0.117 (0.263)	-0.125 (0.137)	-0.240 (0.286)	-0.074 (0.178)
Tax_obs	0.014 (0.203)	-0.407*** (0.077)	0.170 (0.218)	-0.250** (0.097)	0.287 (0.227)	-0.329*** (0.112)
Fin_Lab	0.083 (0.403)	0.559*** (0.208)	0.089 (0.461)	0.382 (0.248)	-0.455 (0.472)	0.304 (0.272)
Fin_Com	-0.070 (0.403)	0.566*** (0.187)	-0.975* (0.558)	-0.002 (0.275)	-0.216 (0.659)	0.285 (0.390)
Fin_Tax	-0.237 (0.310)	0.338** (0.156)	-0.541 (0.414)	0.259 (0.207)	-0.462 (0.516)	0.880*** (0.248)
Lab_Com	-0.392 (0.407)	0.564*** (0.181)	-0.213 (0.455)	0.281 (0.241)	-0.289 (0.487)	0.432 (0.307)
Lab_Tax	-0.198 (0.330)	0.537*** (0.148)	-0.010 (0.352)	0.014 (0.181)	-0.377 (0.336)	0.285 (0.194)
Com_Tax	-0.185 (0.333)	0.501*** (0.142)	0.071 (0.396)	0.022 (0.196)	0.202 (0.434)	0.143 (0.251)
Fin_Lab_Com	0.187 (0.672)	-0.745** (0.348)	1.584* (0.835)	-0.195 (0.465)	0.061 (0.950)	-0.199 (0.586)
Fin_Lab_Tax	0.217 (0.527)	-0.583** (0.282)	-0.472 (0.616)	0.260 (0.342)	0.048 (0.662)	-0.644* (0.375)
Fin_Com_Tax	0.219 (0.568)	-0.779*** (0.265)	0.985 (0.755)	0.250 (0.376)	0.526 (0.872)	-0.512 (0.503)
Lab_Com_Tax	0.456 (0.509)	-0.451* (0.260)	0.242 (0.641)	0.287 (0.336)	0.105 (0.687)	-0.608 (0.408)
Fin_Lab_Com_Tax	-0.676 (0.873)	0.965** (0.453)	-1.077 (1.109)	-0.678 (0.595)	-0.263 (1.213)	0.456 (0.730)
Lnsale2007	-0.006 (0.041)	0.072*** (0.017)	-0.003 (0.052)	0.062*** (0.023)	-0.092 (0.057)	0.121*** (0.025)
Expercent	0.003 (0.002)	-0.001 (0.001)	0.000 (0.002)	-0.003*** (0.001)	0.003 (0.002)	-0.001 (0.001)
Forown	-0.003 (0.002)	0.003** (0.001)	0.003 (0.002)	0.001 (0.001)	0.003 (0.002)	0.001 (0.001)
ISO		0.153** (0.071)		0.154** (0.072)		0.063 (0.076)
RnDdum	0.324 (0.277)	0.768*** (0.064)	0.438 (0.340)	0.846*** (0.072)	-0.336 (0.270)	0.836*** (0.076)
Age	-0.015*** (0.005)	-0.001 (0.002)	-0.019*** (0.004)	-0.001 (0.002)	-0.003 (0.002)	-0.001 (0.002)
Subsidy		0.280*** (0.101)		0.149 (0.101)		0.326*** (0.103)
Regu_time1	0.007*** (0.002)	0.001 (0.001)	0.006** (0.003)	-0.000 (0.001)	0.005* (0.003)	-0.002 (0.002)
Hitech	-0.677 (0.620)	-0.122 (0.386)	0.133 (0.798)	0.583* (0.315)	-0.119 (0.640)	0.341 (0.449)
Constant	-0.293 (0.668)	0.373 (0.358)	-1.056 (1.090)	-0.013 (0.444)	1.215 (1.302)	-1.305** (0.617)
Observations	3,595	1,959	2,263	1,365	1,854	1,184

Standard errors in parentheses

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

Additional variables are included in the selection equation (6.2) to avoid specification problems. These variables are expected to influence the probability of product

innovation but not the new products sales. In reality, such variables are difficult to define (Puhani, 2000; Vella, 1998). ISO and Subsidies will be used to indicate if a firm has an internationally recognized quality certification and received any subsidies from the national, regional or local governments or European Union sources during the period under review. These two factors are used to capture part of the technological capability and additional financial resources of the firms. They are expected to positively influence the probability of participating in and achieving innovation. However, these proxies may not affect the intensity of innovation, as they are mainly determined by the quality of products and services. Finally, three sets of dummies are included to control for size, industry and country specific effects.

6.5 Obstacles to innovation: empirical results

This section discusses the empirical evidence for firms from CEEA countries and elaborates how patterns of obstacles are presented differently across sectors, income levels and size groups.

The complementary/substitutive relationships between pairs of obstacles are tested in the innovation output function with control for firm, industry and country specific effects. A firm's innovation output intensity is measured by the logit transformation of the percentage of sales due to new products and services.

Large volume of sales indicates large scale of production and relatively adequate resources to allocate in production. Firms with a higher turnover are expected to be more innovative compared with firms with small scales of turnover. The estimated coefficients for turnover are significant at 99 per cent for all sub-groups in the selection equation. It suggests that a relatively higher turnover increases the probability of a firm to become an innovator. This effect is more profound in the service sector and the large-sized group, as shown by higher estimated coefficients. However, this positive correlation does not hold with respect to the intensity of innovation. As shown in Table 6.6, Table 6.7 and Table 6.8, the estimated coefficients for variables *Lnsale2007* are insignificant. A firm's age does not affect the innovation propensity and undermines the innovation intensity except for large-sized firms. It is consistent with the argument that old firms are expected to be less dynamic and innovative (Katrak, 1997). This negative effect is strengthened in the service sector and also for firms with fewer than 100

employees. The negative sign of *Ex_percent* in the selection equation implies that exporting firms are less innovative in terms of the new products innovation for manufacturing, upper-middle income and medium size firms. In contrast, positive effects are found for the intensity of innovation. Foreign ownership plays a significant role in stimulating innovation propensity, especially for firms in the service sector and high-income group. These effects are not significant to the innovation sales except for the service sector. The probability for firms with foreign ownership to become successful innovators is higher than for firms with non-foreign ownership.

The R&D dummy indicates whether a firm engages in R&D activities and is included in the innovation output equation. As one of the most important sources of innovation, engaging in R&D is expected to create critical contributions to a firm's innovation performance. The significant coefficients shown in all sub-groups of our study confirm that R&D investment significantly fosters innovator propensity. It is also found that in the service sector, engaging in R&D also strengthens the sales of new products. Firms in high-tech industries have a higher propensity to become innovators in the manufacturing sector. The size of a firm appears to be negative correlated with innovation outcome. Smaller firms are more likely to achieve new products innovation. The estimated coefficients for size dummies are negative and significant in both selection and outcome equation across all groups. The technological capability variable (*ISO*) and external finance variable (*Subsidies*) that are included only in the selection equation appear both as positive and significant.

To sum up, the findings present a clear pattern of the determinants to innovation across sectors. Due to the different nature and operation mechanism between manufacturing and service sector, firm-specific variables have shown rather heterogeneous effects on innovation performance. For instance, foreign ownership plays a more critical role in the service sector in promoting both innovation propensity and innovation intensity. One possible explanation is that new products in the service sector are difficult to succeed without incorporating local culture and customs. Therefore, foreign firms have to carry out innovation activities locally instead of in their home countries. Hence, combined with their adequately skilled labor and efficient management mechanism, the probability of becoming an innovator is likely to be higher for foreign owned firms in the service sector. Meanwhile, we also find out that export intensity only fosters innovation for manufacturing firms. Because it is easy to transfer and imitate, products in the service

sector are less likely to become a tangible product for exporting purposes compared with products in the manufacturing sector. Therefore, the significantly positive effect of the export intensity to innovation is only observed for manufacturing firms.

Table 6. 9 Summary of complementary/substitutive relationships between pairs of obstacles (at 95% significant level)

Dependent variable : R&D	Full Sample	Sectors		Income groups			Size groups		
		Manufacturing	Service	Low & Low-middle	Upper-Middle	High-income	Small (5-25)	Medium (26-100)	Large (>100)
Innovation Propensity									
Fin_Lab	Complementary	Complementary	Complementary	None	Complementary	None	Complementary	Complementary	None
Fin_Com	Complementary	None	None	None	Complementary	None	Complementary	Substitutive	None
Fin_Tax	Complementary	Complementary	Complementary	Complementary	Complementary	None	None	Complementary	Complementary
Lab_Com	Complementary	Complementary	None	Complementary	Complementary	None	Complementary	Complementary	None
Lab_Tax	Complementary	Complementary	Complementary	Complementary	None	Complementary	Complementary	None	None
Com_Tax	Complementary	None	Complementary	Complementary	None	None	Complementary	None	None
New product sales									
Fin_Lab	None	None	None	None	None	Complementary	None	None	None
Fin_Com	None	None	None	Complementary	None	None	None	None	None
Fin_Tax	Substitutive	Substitutive	None	Substitutive	None	None	None	Substitutive	None
Lab_Com	None	Substitutive	None	None	None	None	None	None	None
Lab_Tax	None	None	None	None	None	Complementary	None	None	None
Com_Tax	None	None	None	None	None	None	None	None	None

Turning to the intrinsic relationships between pairs of obstacles, Table 6.9 presents the complementarity/substitutability test results. The test results are based on the likelihood ratio test at the 90 per cent significant level⁸⁹. Four types of obstacles are found to be pairwise complementary with respect to the propensity of innovation when all firms are included. Except for Fin_Com and Com_Tax (at significance level of 95 per cent), other pairwise complementary relationships are all above 99 per cent significant level. The finding is in line with the study from Mohnen and Röller (2005), which confirms the complementarity between financial, labor and tax related obstacles in innovation

⁸⁹ A multivariate one-sided hypothesis test is used in testing complementarity versus substitutability between two obstacles. The test procedure is based on the method introduced in chapter 5. Since the simulation results in chapter 5 show that a method combining HT1 and HT2 in general gives more efficient conclusion, the results in table 6.9 are based on both HT1 and HT2. Specifically, complementarity between two obstacles can be concluded only when one rejects the null hypothesis in HT1 and at the same time accepts the null hypothesis in HT2.

propensity. A complementary relationship suggests that the presence of one obstacle attenuates the deterring effect of the other obstacle. A more intuitive interpretation here would be an additional obstacle does not matter anymore if existing obstacles are already preventing a firm to become a product innovator in EECA countries. Corresponding policy that is on target for removing this additional obstacle would not help the firm to become an innovator. A policy package that is on target for removing all complementary obstacles is favored. Substitutive relations are uncovered between finance and tax obstacles for the sales of new products. Specifically, the existence of finance obstacle worsens the hampering effect of tax obstacles, which begets a lower level of new product sales. In this case, policy instruments that remove only one obstacle individually are preferred because two substitutive obstacles existing simultaneously would aggravate their deterring effects.

Complementarity/ substitutability across sectors

With respect to the innovation propensity, a complementary relation is more likely to be confirmed among finance, labor and tax related obstacles for firms in both manufacturing and service sectors. Informal competition is found to be complementary with labor obstacles for manufacturing firms whereas it shows a complementary relationship with tax obstacles for service firms. There is no complementary or substitutive effect found for firms in the service sector with respect to the intensity of innovation. In the manufacturing sector, substitutability is exhibited among finance and tax, and tax and labor obstacles. In regard to the pattern of these inter-connected patterns (see figure 6.1), labor and tax tend to be connected with other obstacles in forming a complementary relationship.

Complementarity/ substitutability across Income levels

As shown in Table 6.9 (column 5 to 7), in the light of the innovation propensity, the tax obstacle complements the other three obstacles for firms in low- and lower-middle income countries whereas the finance obstacle has the most complementary relationships for firm in middle-income group. Labor and informal competitions are complementary obstacles except for firms in the high-income group. The findings also show that the interactions between obstacles become less intensive as the income level increases. Only labor and tax are found to be connected as complementary factors in the high-income group. Turning to the innovation intensity, relatively few interactions are observed.

Finance and informal competition are complementary for firms in low and lower-middle income countries. And a substitutive relationship is found between finance and tax obstacles for the same group. The labor obstacle appears to be more active for high-income group because it forms complementary relationships with both finance and tax.

Complementarity/ substitutability across firm size

Except for finance and tax, other types of obstacles are confirmed to be complementary to innovation propensity for firms with 5 to 25 employees. Finance obstacle seems to have a complementary relationship with both labor and tax while it exhibits a substitutive relationship with informal competition for firms with 26 to 100 employees. Furthermore, labor and informal competition are observed as complementary obstacles in this group. Only one complementary relationship is found for firms with more than 100 employees, which is between finance and tax. Looking at the pattern of connections between obstacles, less intensive interactions are shown with respect to the innovation intensity. Only one interaction is observed substitutability between finance and tax for medium-sized firms.

Overall, there seems to be a clear picture concerning the patterns of obstacles in different sectors, income levels and size groups. First, based on the number of connections, complementary relationships between obstacles dominate the pattern with respect to the propensity of product innovation. Fin_Tax appears most frequently across all sub-groups compared with other pairs of obstacles. It is followed by Fin_Lab, Lab_Com and Lab_Tax. Considering the innovation intensity, substitutability tends to be formed, especially by Fin_Tax. Secondly, complementary or substitutive relationships between obstacles are less frequent for firms from higher income countries or with larger number of employees. One possible explanation is that firms from high-income countries or with many employees are comparatively more resource abundant, either financial-wise, in skilled labor or through their past experience. They are less likely to encounter obstacles in the innovation process, as well as interactions between obstacles. Last, the estimated coefficients for obstacles in the outcome equation most often have a positive sign. Such a finding might turn up because firms learn about obstacles as they become more innovative. Thus, as the intensity of innovation increases (a higher percentage of sales due to new products or services), the firm is expected to perceive more obstacles.

Figure 6.2 Complementarity/substitutability between obstacles to innovation propensity

6.6 Conclusion and policy remarks

By investigating the potential complementarity and substitutability between obstacles, we are able to obtain a clear picture on how obstacles interact with each other in determining firms' innovation performance. With inadequate resources to eliminate all barriers together, especially for firms in developing countries, understanding the intrinsic relationships between obstacles is essential to formulate efficient strategies and policies.

Despite the fact that R&D is often seen as the key source to a firm's technological upgrading, not all firms are willing to engage in R&D activities. There are about 73 per cent of EECA firms in our sample that do not engage in R&D. The estimation confirms that R&D investments foster a firm to become an innovator. Furthermore, we adopted the generalized Tobit model, which enables us to differentiate obstacles to innovation propensity from obstacles to innovation intensity. The findings show that four types of obstacles are complementary with respect to the propensity of innovation. It suggests that an additional obstacle does not matter anymore if existing obstacles are already preventing a firm to become a product innovator. Hence, policy instruments should be designed to eliminate them together rather than removing them individually. In contrast, a substitutive relation in which mainly exist between finance related and tax related obstacles plays a dominant role regarding the innovation intensity. Under these circumstances, the presence of one obstacle (e.g. high tax rate) would exacerbate the undermining effects induced by the other obstacle (e.g. inadequate internal finance). Policies that intend to remove them individually would be preferred.

Without obtaining the full information on process innovation, the current study is constrained to look only at product innovation. Other technological sourcing is also critical for firms in EECA countries since only 27 per cent of firms engage in R&D and there are about 58 per cent of firms that claims to have product innovation. At least 29 per cent of sampled firms adopt other channels as technological sourcing than R&D investment, which might cause a potential missing variable bias in estimating the innovation function. Another limitation of this study is that some firms might learn to cope with obstacles by innovating instead of realizing obstacles beforehand, which could explain the positive coefficients for obstacle variables in the innovation intensity function. Last, without computing the marginal effects of each obstacle by taking the potential complementarity into account, we cannot give concrete policy suggestions on the sequence of removing obstacles.

Appendix 6A

Type of obstacles	No.	Percentage
Access to finance	1,293	16.77
Access to land	178	2.31
Business licensing and permits	231	3
Corruption	459	5.95
Courts	96	1.24
Crime, theft and disorder	146	1.89
Customs and trade regulations	184	2.39
Electricity	352	4.56
Inadequately educated workforce	891	11.55
Labor regulations	183	2.37
Political instability	778	10.09
Practices of competitors in the informal sector	830	10.76
Tax administration	270	3.5
Tax rates	1,349	17.49
Transport	96	1.24
Does not apply	376	4.88
Total	7,712	100

No.: The number of firms which report the biggest obstacle faced by the establishment

Chapter 7

Conclusion

7.1 Summary

The present thesis sheds light on the potential synergistic effects of innovation strategies and policies in developing countries. The findings have contributed to expanding our understanding of complementarity assets that potentially exist in innovation. Our main concerns are placed on investigating the interdependent relationships between technological sourcing strategies, and also the potential interactions between innovation obstacles. Furthermore, this thesis also contributes to the methodology in testing complementarity in the case of more than two activities. By comparing two commonly used one-sided multivariate hypotheses, we provide a detailed discussion of their potential problems and statistical power, and also give implications on which hypothesis should be adopted based on different model specifications. The Investment Climate Survey from the World Bank has been used as the main data source for the empirical analyses. Here we highlight our findings.

Technological sourcing

The lack of advanced technological competencies in developing countries requires innovation to occur through the imitation or adoption of already existing technologies. Especially in low-income countries, the low levels of technological capability severely constrain firms to close their distance from the technological frontier. Most of them rely on external knowledge acquisitions to engage in innovation activities from a basic level.

By using firm-level data across 24 developing countries, chapter 4 examines the significant contribution of external technological sourcing exert to productivity growth in low-income countries. In this context, firms tend to rely on acquiring technology externally such as licensing, imported machinery and the like. The technological sourcing trajectory changes as the level of development goes up. In the context of middle-income countries, firms have already built up certain parts of innovation capabilities and also have gained innovation experience. In-house R&D activities start paying off in terms of generating higher level of productivity. The findings also exhibit that in-house R&D strengthens the benefits of external technological sourcing. A synergistic effect is uncovered when firms adopt both internal and external technological sourcing simultaneously.

Considering the different development paths and country specificities, innovation behaviors and technological sourcing trajectories vary across countries. Chapter 3 takes a closer look at the technological sourcing in Chinese manufacturing firms. Classified as a middle-income country, China has accumulated basic innovation capabilities through external and internal channels. Firms are found to benefit from doing both R&D and technology purchasing in raising the sales of new products per employee, but the complementarity is only observed in small-sized Chinese manufacturing firms with 100 to 300 employees. The findings confirm that in-house R&D accelerates the assimilation of external know-how while external technology sourcing enhances the efficiency of in-house innovation activities, which is consistent with the conclusion drawn from Chapter 4.

In relation to complementarity, there might have to be a minimum of technological capability for it to work out. Without a basic level of absorptive capacity or certain accumulation of R&D, importing technology does not pay off in terms of productivity improvement. Therefore, government and corporate policies should be formulated on the basis of specific learning mechanisms underlying different levels of development. At a low level of development, external technological sourcing is essential for firms to gain a basic capability accumulation. Governments should draw up policies that encourage firms to acquire technology externally, such as providing technological information and financial support for technology import. In middle-income countries where firms have built up certain level of technological capabilities and gathered some innovation

experience, government policies should stimulate firms to invest in innovation by both internal and external channels.

Innovation obstacles

Studies with respect to innovation have devoted great emphasis to the determinants, capability and consequence of innovation in both advanced and developing economies. Less attention has been paid to which barriers block innovation or cause innovation failures at the firm level. Such neglect is particularly notorious in the context of developing countries. Due to relatively severe institutional, resource and affordability constraints, firms from developing countries are likely to face more barriers in the learning process. By investigating the potential interdependent relationships between pairs of obstacles on the ICS EECA 2008 data, Chapter 6 tries to identify factors that severely constraint innovation in Eastern European and Central Asian countries. The empirical analysis uncovers the potential complementary between innovation obstacles. It helps us to obtain a clearer picture about how obstacles interact with each other in determining firms' innovation performance and consequently provide policy implications.

The findings show that four types of obstacles (finance, tax, skilled labor and competition from the informal sector) are found to be pairwise complementary with respect to the propensity of innovation for firms from EECA countries. A complementary relation suggests that policy packages that attempt to eliminate them together are preferred. Only removing one of them would amplify the deterring effects of the other. When it comes to the innovation intensity, substitutive relations are uncovered between finance and tax, labor and tax obstacles in terms of new product sales. A substitutive relationship suggests us removing at least one obstacle because its presence would magnify the undermining effects induced by the other. Policies that attempt to avoid obstacles appearing simultaneously would be preferred in this case.

Complementarity with more than two activities

The perspective of complementarity is intriguing, yet it lacks the specificity about its definition, classification and testing approach framework. Chapter 2 reviews the general definition of complementarity and it gives a clear hierarchy classification. Based on different types of complementarity, different testing approaches are also given. Chapter 4

compares the behavioral complementarity and objective complementarity by distinguishing complementary effects from the correlation caused by unobserved heterogeneity. When one tries to test complementarity among three or more activities in a linear model, multiple inequality restrictions are imposed on the estimated parameters and the corresponding statistical inferences are provided by multivariate one-sided hypotheses. Chapter 5 explains how to implement the PROD approach in an objective function with more than two activities. It focuses on the different hypotheses used for testing coefficients under multiple inequality constraints. A simulation experiment is employed and the findings reveal the potential biases which may exist in different types of multivariate one-sided hypotheses in testing for complementarity. The result also highlights that combining two hypotheses together always guarantees a more accurate conclusion. However, for a better-specified model with a relatively large sample size (e.g. larger than 1000), only one individual hypothesis will also perform consistently and generate an efficient result.

7.2 Limitations and further research

The contextual conditions, main technological activities and the nature of innovation output differ significantly between innovation in developed countries and developing countries. As a result, firms in these country groups adopt technology for different purposes and use it rather differently. Empirical studies of firms' innovation behavior usually require the availability of relatively sound datasets. Even though the Investment Climate Survey from World Bank provides us a unique opportunity to conduct comparison analysis, yet information with respect to innovation behavior at firm level is still limited, especially for the latest waves. Apart from having limited innovation information, observations are also largely unbalanced across each wave, which rules out the possibility of conducting panel data analysis. Systematic surveys with standard methodology and survey instruments (e.g. Community Innovation Survey in Europe) across developing countries are needed for future research.

Due to the inaccessibility of more advanced innovation data in developing countries, cross-sectional analyses are adopted in most parts of this thesis. The potential problem is the endogeneity of input variables such as capital, labor and knowledge inputs, which may be correlated with unobserved factors in the residual. Additionally, without

longitudinal analysis, the time-invariant individual effects may also produce inconsistent estimations.

With respect to complementarity studies, an important point worth mentioning is that significant differences in results are found by adopting different testing approaches (e.g. chapter 2, chapter 4 and chapter 5). For example, conclusions based on the Correlation approach and Production approach are most likely to be different because the former is formulated to test “behavioral complementarity” and the latter is to test “objective complementarity” (see chapter 2.3), the same for the Miravete/Pernías approach and the Production approach (see chapter 4.3). In the cases of testing complementarity with more than two activities, results are also significantly different by using single-cross term, all-cross term and full-cross term approaches (see Chapter 5). Future studies should be aware of distinguishing these testing approaches.

The notion of complementarity has a potentially major application in explaining consistency in economic performance and organizational stability. As mentioned by Ennen et al. (2009), complementarities arise in a complex environment involving various elements. Those elements include not only activities, which are complementing each other, but also factors that accommodate or inhibit the emergence of complementarities. Relatively fewer studies try to investigate the condition or the cause of complementarity. Future studies should try to pay more attention to the preconditions and contextual factors, both internal and external, which accommodate complementarity instead of merely concentrating on the synergistic outcomes. Another challenge for future research is to identify which sub-group of activities plays the core role in connecting a complementary system and which activities can be broken off without influencing the performance? Moreover, most empirical studies on complementarity are based on a cross-sectional perspective. Further research should pay greater attention to outcomes based on longitudinal analysis.

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Samenvatting

Deze samenvatting introduceert het onderwerp van dit proefschrift en beschrijft de data die zijn gebruikt voor de empirische analyse. Het geeft vervolgens een beknopte weergave van de resterende hoofdstukken.

Het tweede hoofdstuk poogt het concept van complementariteit te begrijpen en beschouwt eerdere studies over innovatie in de bestaande literatuur die de complementariteit benadering toepassen. Het geeft een inzichtelijke interpretatie weer van complementariteit tussen paarsgewijze economische activiteiten door een hiërarchische classificatie te gebruiken. Complementariteit wordt over het algemeen ingedeeld in twee categorieën die gebaseerd zijn op al of geen inkadering in een specifieke objectieve afhankelijkheidsrelatie: objectieve complementariteit en gedragsebepalende complementariteit. Een nadere classificering in de lagere hiërarchie wordt tevens gedefinieerd. Naast het uitwerken van verschillende typen complementariteit introduceert hoofdstuk 2 ook de benaderingen zoals die in empirische studies worden toegepast om complementariteit en substitutie te toetsen. Drie benaderingen worden onderscheiden: CORR (correlatie benadering), MP (Miravete en Pernías benadering) en PROD (productie benadering). Bovendien komt uit de bestudering van de studies, die complementariteit in innovatieprocessen trachten te onderzoeken, de problemen en beperkingen naar voren die thans in de literatuur bestaan. Het hoofdstuk betrekking hebbende op het literatuuroverzicht verstrekt een gedetailleerde discussie over deze problemen en beperkingen. Het verklaart ook op welke wijze deze in dit proefschrift zullen worden behandeld.

Hoofdstuk 3 onderzoekt het bestaan van complementariteit tussen *in-house* R&D en externe technologische acquisitie door panel data van Chinese productiebedrijven te gebruiken. Het tracht het effect te onderzoeken van interne en externe technologie

inkoop op de bedrijfsinnovatie en productiviteit in kleine en middelgrote Chinese productiebedrijven. Het voorspelt in het bijzonder de opbrengst van R&D en de aankoop van externe technologie en de mogelijke complementariteit of substitutie ertussen. Dat doet het door onderscheid te maken tussen twee prestatiemaatstaven, te weten innovatie in producten of processen en arbeidsproductiviteit. Omdat grootte in dit geval relevant is, schatten wij afzonderlijk de relaties voor bedrijven met minder dan 100, tussen 100 en 300 en meer dan 300 werknemers. De resultaten laten zien dat *in-house* R&D de assimilatie van externe knowhow lijkt te versnellen terwijl de inkoop van externe technologie de efficiëntie van *in-house* innovatie versterkt. De resultaten laten ook enig bewijs zien voor het bestaan van complementariteit van *in-house* R&D en de aankoop van externe technologie in de toename van de verkoop van nieuwe producten per werknemer in kleinschalige Chinese productiebedrijven tussen de 100 en 300 werknemers, terwijl R&D en de aankoop van externe technologie substituten zijn als het gaat om de toename van de arbeidsproductiviteit.

Het vierde hoofdstuk beschrijft een andere empirische studie die potentiële synergetische effecten tussen technologische strategieën toetst, gebruikmakend van *cross-sectional* data van bedrijven uit 24 ontwikkelings- en minst ontwikkelde landen. In dit hoofdstuk pogen wij factoren te identificeren die de keuze voor de inkoop van specifieke technologie bepalen alsmede factoren die potentiële complementariteit bevorderen. Het bestudeert de functies van interne R&D inspanningen en de inkoop van externe technologie met betrekking tot het bevorderen van de productiviteit van productiebedrijven. Drie benaderingen worden vergeleken en toegepast in de empirische analyse, zijnde CORR, PROD en MP (Miravete en Pernías benadering, zie hoofdstuk 4). De analyse benadrukt dat in een *cross-sectional* analyse de MP benadering ten opzichte van de andere twee benaderingen opvalt omdat het een structureel kader verschaft dat op effectieve wijze de afwijking corrigeert die veroorzaakt wordt door de correlatie tussen zgn. *unobservables*. De empirische bevinding laat de kritische rol zien van de acquisitie van externe technologie voor fabricage industrieën in ontwikkelingslanden en toont tekenen van complementariteit in alleen midden-inkomenslanden. De bevindingen geven ook aan dat verschillende benaderingen verschillende resultaten voortbrengen.

Hoofdstuk 5 bediscussieert de verschillende vormen van multivariate eenzijdige hypothese gedefinieerd om paarsgewijze complementariteit tussen drie of vier activiteiten te toetsen. Dit hoofdstuk gebruikt gesimuleerde datasets om de validiteit en efficiëntie te

vergelijken van twee type hypothesen met verschillende modelspecificaties en steekproefgrootte. De simulatieresultaten bevestigen the potentiële afwijking die zou kunnen bestaan in het formuleren van een *non-exhaustive* hypothese. Conclusies die gebaseerd zijn op dergelijke hypothesen, neigen af te wijken indien geen rekening wordt gehouden met de aard van de ongelijkheden. Resultaten uit dit hoofdstuk suggereren ook dat het combineren van twee hypothesen altijd een meer accurate conclusie in het toetsen van complementariteit garandeert. In een enkele situatie, specifiek in het geval van een grote steekproefomvang en een hoge waarde van R-square voor lineaire modellen, kan ook het testen van slechts één hypothese adequate informatie geven voor het trekken van juiste conclusies.

Teneinde de barrières voor innovatie beter te kunnen begrijpen, past hoofdstuk 6 de complementariteitsbenadering toe op bedrijfsniveau gegevens uit de Investment Climate Survey 2009 Eastern European and Central Asian countries (EECA) om te onderzoeken in hoeverre er complementariteit dan wel substitutie bestaat tussen vier categorieën van innovatie-obstakels in verschillende sectoren, over inkomensniveaus en groepsgrootte. De benadering van de paarsgewijze complementariteitstoets, indien er sprake is van meer dan twee activiteiten, is ontleend aan hoofdstuk 5. De resultaten uit dit hoofdstuk geven een duidelijke verklaring voor de complementariteit tussen barrières voor innovatie: de aanwezigheid van een obstakel verzacht het belemmerende effect van het andere obstakel voor innovatie. De bevinding suggereert dat beleidsmaatregelen die beide obstakels trachten aan te pakken, de voorkeur genieten. Beleid dat slechts één obstakel wegneemt, zal het tegenwerkende effect van de ander vergroten. Een substitutie relatie tussen obstakels, aan de andere kant, suggereert dat het verwijderen van één obstakel voldoende is omdat het niet wegnemen ervan de negatieve effecten veroorzaakt door het andere obstakel zou versterken.

Het laatste hoofdstuk sluit dit proefschrift af met het duiden van enkele beleidsimplicaties en het adviseren over richtingen voor toekomstig onderzoek.

Curriculum vitae

Jun Hou was born on February 1982 in Guiyang, China. He finished his bachelor course in Agricultural Economics at Southern China University of Tropical Agriculture (Hainan University). In 2007, he obtained his MA in Economics of Development at the Institute of Social Studies, Erasmus University, Rotterdam, and later that year, joined the PhD program at UNU-MERIT, Maastricht University. Jun Hou is currently employed as a research officer at the TMD center, Oxford Department of International Development, Oxford University.

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