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From knowledge linkages to value added: using the lens of ?innovation value chain? on the comparison of high- tech and low- tech industries

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Abstract

Knowledge has always been an important determinant of innovation with its contribution to economy. Innovation value chain (IVC) is a model to identify characteristic of knowledge and highlight the determinants of innovation to generate value added outputs. The previous research have examined the innovation value chain (IV) at the scale of a country such as United Kingdom (Roper et al., 2008), the focus on a specific sector like new-technology based firms (Ganotakis and Love, 2011) and the comparing different regions of Ireland and Switzerland (Roper and Arvanitis, 2009) but the lack of the comparison on the difference between high- tech and low- tech sectors. To bring a more understanding of the difference between firms in high- tech and low- tech industries on the whole innovation process from knowledge linkages to value added, innovation value chain is used as the lens for the investigation. Therefore, 1806 innovative manufacturing firms were derived from 2nd Taiwanese innovation survey with 910 firms in high- tech industries and 896 firms in low- tech industries. The result shows that firms in high- tech industries tend to search knowledge from suppliers and competitors to complement their internal R&D for product innovation while firms in low- tech industries are more likely to derive knowledge from customers for process innovation. Moreover, product innovation in high- tech industries positively influences on a firm?s employee growth.

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Abstract

Knowledge has always been an important determinant of innovation with its contribution to economy. Innovation value chain (IVC) is a model to identify characteristic of knowledge and highlight the determinants of innovation to generate value added outputs. The previous research have examined the innovation value chain (IV) at the scale of a country such as United Kingdom (Roper et al., 2008), the focus on a specific sector like new-technology based firms (Ganotakis and Love, 2011) and the comparing different regions of Ireland and Switzerland (Roper and Arvanitis, 2009) but the lack of the comparison on the difference between high- tech and low- tech sectors. To bring a more understanding of the difference between firms in high- tech and low- tech industries on the whole innovation process from knowledge linkages to value added, innovation value chain is used as the lens for the investigation. Therefore, 1806 innovative manufacturing firms were derived from 2nd Taiwanese innovation survey with 910 firms in high- tech industries and 896 firms in low- tech industries. The result shows that firms in high- tech industries tend to search knowledge from suppliers and competitors to complement their internal R&D for product innovation while firms in low- tech industries are more likely to derive knowledge from customers for process innovation. Moreover, product innovation in high- tech industries positively influences on a firm's employee growth.

1. Introduction

In this knowledge economy era, knowledge as the asset of a firm is considered as important inputs of innovation to maintain the competitiveness. At the beginning of innovation research, R&D was considered as the only and vital input of innovation activities and the linkage to technical change (Crépon et al., 1998; Lööf and Heshmati, 2001 and 2002). As ‘high- tech’ represents a sector with higher R&D intensity, it has always been an important sector as a focus of innovation research (Freeman and Soete, 1997). Despite the fact of higher R&D intensity in high- tech sectors, low- tech sectors also engage in R&D activities (Hatzichronoglou’s 1997). However, the extent of resources driving innovation has been stretched outside organizational boundary, and R&D has been criticized not the only determinant of innovation success (Chesbrough, 2003 and 2006). More and more researchers start to attach a higher importance to low- and medium- tech sector (Bender, 2004; von Tunzelmann and Acha, 2005; Robertson and Patel, 2007; Tsai and Wang, 2009). Low- tech sector hence reveals the value and importance to innovation research.

Although more research have paid attention on innovation activities in low- tech sector, there are a few research comparing the difference between high- tech and low- tech sectors. Hauknes and Knell (2009) argued that high- tech sector is usually considered as more technology producing industries while low- tech is more technology using industries, and the different requirements between high- tech and low- tech sectors cause various knowledge sourcing behaviours. It has been demonstrated that the knowledge searching pattern to innovation differs between high- tech and low- tech industries. The search pattern of firms in high- tech industries has been found more technology-oriented knowledge while firms in low- tech industries access more market knowledge (Grimpe and Sofka, 2009).

Innovation value chain (IVC) is a model to identify characteristic of knowledge and highlight the determinants of innovation to generate value added. The previous research have examined the innovation value chain (IV) at the scale of a country such as United Kingdom (Roper et al., 2008), the focus on a specific sector like new-technology based firms (Ganotakis and Love, 2011) and the comparing different regions of Ireland and Switzerland (Roper and Arvanitis, 2009) but the lack of the comparison on the difference between high- tech and low- tech sectors. Therefore, 1806 innovative manufacturing firms were derived from 2nd Taiwanese innovation survey with 910 firms in high- tech industries and 896 firms in low- tech industries. The main purpose of this study is to investigate the different knowledge searching strategies applied in high- tech and low- tech industries to lead to added value end of innovation activities.

2. High- tech and low- tech industries

There is no united global standard which classifies high- tech and low- tech industries because of the differences between regions and technological environments. The majority of research and projects refer to OECD approaches to classify industries and take R&D intensity as the indicator of high- tech and low- tech sectors. Hatzichronoglou (1997) extends the approach to classify industry by using three major methods, which are sector, product and pattern approaches. The sector approach considers high- tech industry as the high- tech manufacturing sector, medium high- tech manufacturing sector, and high- tech knowledge-intensive service while the product approach can take into account the characteristics of high- tech products. For the patent approach, high tech is regarded as high- tech patents and biotechnology patents. (Hatzichronoglou, 1997; Peneder, 2003; Eurosat, 2008)

Focusing on manufacturing industries, Hatzichronoglou (1997) categorizes all manufacturing industries into four groups, high- tech, medium and high- tech, medium and low- tech and low- tech. These industries are classified by the sector approach based on the degree of technology intensity (the ratio of R&D expenditure to value added). Furthermore, Hatzichronoglou (1997) also defines a list of high- tech products by the product approach and introduces as aerospace, computers- office machines, electronic- telecommunications, pharmacy, scientific instruments, electrical machinery, non- electrical machinery and armament.

There is no clear boundary to classify high- tech industries in Taiwan. Taiwanese Government lists ten emerging industrial orientations based on high value added, high techniques/skills, low pollution and low dependence on energy. These ten industries are related to communication, information technology (hardware and software), consumer electronics, semiconductor, precision and automatic machinery, aerospace, pharmaceuticals and biotechnology, medical machinery, environmental engineering and construction, and high technical materials. Based on these emerging industries, more specific products are considered as an individual industry because of the growth of productivity in some sectors.

To define high- tech industries in Taiwan, Taiwanese Government takes account of input (R&D intensity and R&D employee/total employee) and output (technique and labour productivity) dimensions. Based on the above two indicators and the growth of production within these emerging industries mentioned above, the Ministry of Economic Affairs considers electronics and electrical machinery (Information Industry, semiconductor, consumer electronics, communication and optoelectronics), Chemicals, Biotechnical industry and precision machinery as Taiwanese high- tech industries (Taiwan Ministry of Economic Affairs, 2001). Based on the classification of Taiwanese manufacturing industries, this research includes five high- tech industries and the rest are defined as eight low-tech industries which are named as traditional industries in Taiwan. Table 1 shows the list of Taiwanese high- tech and low- tech manufacturing industries classified by this research.

5. Conceptual framework

Innovation value chain (IVC) is a recursive model from knowledge linkages to value added. The whole innovation process can be divided into three steps, knowledge sourcing, knowledge transformation and knowledge exploitation. The argument here is that there are different knowledge searching patterns between high- tech and low- tech industries to derive external knowledge and develop internal knowledge for innovation activities (Grimpe and Sofka, 2009). Moreover, from the resource based and capability perspectives, there are some factors might shape the three steps of IVC and it could be different between high- tech and low- tech sectors due to different characteristics of innovation and development (Hauknes and Knell, 2009). The whole structure of innovation value chain can be viewed in figure 1.

5.1 Knowledge sourcing

The first step of IVC is knowledge sourcing activities with the factors which shape the interaction between these knowledge linkages. Internal R&D in the past was recognised as the only source of knowledge for innovation (Crépon et al., 1998; Lööf and Heshmati, 2001 and 2002). However, the extent of innovation activities has stepped outside an organization which is supported by the argument of open innovation (Chesbrough, 2003 and 2006). The linkages to external knowledge have become obvious and important either with substitution relationship (Schmidt, 2010; Love and Roper, 2001) or complementary relationship (Cassiman and Veugelers, 2002; Roper and Love, 2005; Roper et al., 2008 and Ganotakis and Love, 2011).

Based on the previous literature, there are seven different types of knowledge sourcing linkages identified here that might affect a firm’s innovation: internal R&D (Shelanski and Klein, 1995; Roper et al., 2008; Hsieh et al., 2011), external R&D (Veugelers and Cassiman, 1999; Hsieh et al., 2011), forward linkages to customers (Joshi and Sharma, 2004; Roper et al., 2008), backward linkages to either suppliers or consultants (Horn, 2005; Smith and Tranfield, 2005; Roper et al., 2008), horizontal linkages to either competitors or other companies (Hemphill, 2003; Link et al., 2005; Roper et al., 2008), public linkages to either universities or public research centres (Roper et al., 2004; Del Barrio-Castro and Carcia-Quevedo, 2005) and informal linkages to exhibitions, professional association or technical standards (Harris and Li, 2009; Reychav, 2009).

The beginning of IVC is modelled as the below equation in order to evaluate the probability that a firm will engage in each of the seven knowledge sourcing activities. Two estimations are carried out with one group of high- tech industries and another group of low- tech industries.

$$KS^*_{ji} \equiv \beta' KS_{ki} + \gamma'_0 RI_{ji} + \gamma'_1 CI_{ji} + \gamma'_2 GFS_{ji} + \gamma'_3 EX_{ji} + \varepsilon_{ji}, \quad j,k \equiv 1,7$$

$KS_{ji} = 1$ if $KS^*_{ji} > 0$; $KS_{ji} = 0$ otherwise, (Eq. 1)

where; KS_{ji} stands for the i_{th} firm's knowledge sourcing activity j (or k), and $j,k = 1,2,3,4,5,6,7$, $i = 1,......,n$. The error term ε_{ji} is assumed to follow a multivariate normal distribution with mean zero and variance-covariance matrix V, where V has values of 1 on the leading diagonal and $\rho_{jk}=\rho_{kj}$ for $j \neq k$. KS_{ki} represents the firm's other knowledge sourcing activities. If β is positive this would suggest a complementary relationship between the knowledge sourcing activities; negative β would suggest a substitute relationship. RI_{ji} and CI_{ji} are two sets of indicators of the firm's resource base and capacity, as indicated earlier. γ_0 is expected to be negative as the argument of resource- based view suggests that stronger internal resource will reduce the requirement of external knowledge. GFS_{ji} reflects access to government financial support for innovation and upgrading, and the coefficient here (γ1) is expected to be positive. The last element, EX_{ji}, is included in order to control for the exporting behavior of the observed firms. Except domestic environment and organizations, firms can derive knowledge from other countries through export activities. It has been argued that knowledge can be derived during exporting (Love and Ganotakis 2010).

5.2 Innovation activities

The second step of the IVC is innovation production which is the process of knowledge transformation. A firm interprets the external knowledge and employs it to value added. Because of the different characteristics between high- tech and low- tech industries, it has been suggested that there are different knowledge linkages leading to innovation decisions and success. Firms in high- tech industries tend to access universities or supplier to derive technological knowledge while firms in low- tech industries are more likely to benefit from the knowledge provided by customers or competitors (Grimpe and Sofka 2009). An assumption here is raised that different knowledge sourcing behaviour for innovation exist in high- tech industries from low- tech industries. Therefore, the comparison of the innovation production function between high- tech and low- tech industries is listed as the below:

$$I_i = \phi_0^{'} KS_{ki} + \phi_1 HD_i + \phi_2 KS_{ki} HD_i + \phi_{3^{'}} RI_i + \phi_4^{'} CI_i + \phi_5 GFS_i + \phi_6 EX_i + \varepsilon_i \quad \text{(Eq 5.2)}$$

Where I_i is an innovation output indicator (k=1,…,7), that indicates the alternative knowledge sources identified earlier, HD_i is a dummy variable of high- tech industries, $KS_{ki}HD_i$ is an interaction term representing firms with KS_k in high- tech industries. RI_{ji} and CI_{ji} are two sets of indicators of the firm's resource base and capacity, as indicated earlier. GFS_{ji} reflects access to government financial support for innovation and upgrading so the coefficient here (ϕ_3) is expected to be positive. EX stands for a dummy variable of export, ε_i is the error term and other variable definitions are as above.

5.3 Innovation outputs- value added

The last step of IVC is the knowledge exploitation which leads to firm performance influenced by innovation (Geroski et al., 1993). Because the process innovation provided an indirect link between knowledge sourcing activities and performance, the augmented production adopted in this valued added process measures together both product and process innovation. The assumption raised here is to investigate if innovation happening in high- tech industries has significant effect on firm performance and the equation is listed as the below.

$$BPERF_i = \lambda_0 + \lambda_1 INNO_i + \lambda_2 HDi + \lambda_3 INNO_i HD_i + \lambda_4 X_i + \tau_i \qquad \text{(Eq. 5.3)}$$

Where *BPERFi* is an indicator of business performance (e.g. productivity, sales growth or employment growth), *INNOi* is a vector including innovation outputs measures for both process and product innovation, HD_i is a dummy variable of high- tech industry, $INNOiHD_i$ is an interaction term representing a firm with *INNOi* belonging to high- tech industries, and *Xi* is a set of firm specific variables that are hypothesized to have effect on firm performance.

3. Data

The data for the empirical analysis is adopted from 2nd Taiwanese Innovation Survey (TIS) which provides the information of innovation activities, their knowledge sourcing activities and firm's basic information over the period 2004 to 2006. The design of TIS2 was based on the 4th Community Innovation Survey by OECD (Organisation for Economic Co-operation and Development) and the consideration of Taiwanese specific industry environment and issues. Moreover, the sample was proportionally and randomly selected from all the manufacturing industries in Taiwan based on the whole population of manufacturing firms identified by the Industry, Commerce and Service Census conducted by the Taiwanese government. There are 1806 innovative manufacturing including 910 firm in high- tech industries and 896 firms in low- tech industries.

The table 2 summary statistics highlights that some significant difference of the listed variables between high- tech and low- tech industries by carrying out independent sample t- test. Therefore, the significant difference of IVC between high- tech and low- tech industries reveals. The result shows that product innovation (decision and success) is significantly different between high- tech and low- tech industries with 62% of product innovative firms in high- tech industries and 48% in low- tech industries. What surprises here is although there is a significant difference of the decision of internal R&D between high- tech and low- tech industries, the percentage of internal R&D shows none. It highlights the fact that those firms in low- tech industries have high percentage of R&D investment although much fewer of firms internal R&D with the average product innovation success 57.2% while 61.1 in high- tech industries. Most knowledge sourcing activities show a significant difference between high- tech and low- tech industries except external R&D and the linkage to customers. It shows the most knowledge linkage in both high- tech (85%) and low- tech industries (79%) is internal R&D. The rest knowledge linkages are in sequence with forward linkage (high- tech: 74%; low- tech: 72%), informal linkage (high- tech: 71%; low- tech: 55%), backward linkage (high- tech: 70%; low- tech: 55%), horizontal linkage (high- tech: 63%; low- tech: 56%), public linkage (high- tech: 56%; low- tech: 39%) and external R&D (high- tech: 32%; low- tech: 28%). Although there is slightly different in the sequence of knowledge linkages in low- tech industry, it is consistent with the most sequence with high- tech industry.

4. Method

At the first step of IVC, seven different types of knowledge sourcing activities are proposed to estimate the simultaneous knowledge sourcing equation (eq. 1). It was proposed by Ashford and Sowden (1970) to estimate several correlated binary variables jointly where multivariate probit (MVP) is the most efficient approach to be carried out in this estimation. However, as Greene (2005)'s argument that the efficiency gained from MVP will reduce when the vectors of independent variable are strong correlated. Although the proposed knowledge linkages are sourced from different sources, the added potential for simultaneous between these knowledge sourcing activities are similar. Moreover, there are other some issues which show that the difficulties MVP could face when it is survey-based data. Firstly, the statistical efficiency gain from using simultaneous estimation approach will be offset because of large number of missing data. Secondly, in practice, achieving convergence with an MVP estimator places some limits on the degree of simultaneity which it is possible to include. However, what the research interests here is the complementary or substitute relationship between knowledge sourcing activities. Thirdly, the derivation of marginal effects is important in order to gain a better understanding of the innovation value chain and MVP is less straightforward in relation to simpler modelling framework.

Furthermore, one of the main purposes in this study is to compare the difference between high- tech and low- tech industries. In this equation, two groups of high- tech and low- tech industries are estimated separately rather than to set up the interaction term because the study interests at this stage is to see if there is any difference of the knowledge sourcing patterns between high- tech and low- tech industries.

Therefore, seven single probit models are used individually in high- tech and low- tech industries. Although the statistical efficiency are reduced, this approach provides substantial gain in terms of the number of valud observations, the ability to reflect more fully the relationship between knowledge sourcing activities and the ability to identify readily interpretable marginal effect.

Appropriate estimation approaches are chosen here depending on the nature of the dependent variable of the equation (eq. 2). When the indicator of innovation is product or process innovation decision (dummy varibale), bivariate probit model is adopted while tobit model is applied when the measurement is innovation success with upper and lower bounds (McDonald and Moffitt, 1980). Moreover, linear OLS regression model is adopted to estimate firm performance at the last step of innovation value chain.

There are two econometric issues can be raised here for the discussion. Whether if heterogeneity exists in performance results and whether there is potential endogeneity of the innovation output measure. It has been argued that a survey data even in narrowly defined industries still can be very large variations existing in business performance (Caves, 1998) Lööf and Heshmati (2002)'s empirical study supports this statement and one outcome of the heterogeneity issue is sample selection. The purpose of this study is to compare high- tech and low- tech industries so the investigation here is to check if the observed innovative firms can be regarded as their representative groups. The Heckman test is a simple test of the null hypothesis of no sample selection bias (Heckman, 1979), so it is used here to investigate the existence of sample selection bias for the case of innovation success. Another issue of potential endogeneity of innovation output measures in models of business performance has been discussed in the literature and the potentional approaches adopted include two-stage estimation method (Crépon et al., 1998) and the simultaneous estimation of the innovation and augmented production functions (e.g. Lööf and Heshmati, 2002). In this study, Hausmand tests are carried out for different specifications of a firm's innovation activities (product and process innovation decision and innovation success) and the measures of firm performance (sales growth, employee growth and productivity). The result of the above tests for this study show there is neither sample bias problem nor endogeneity issue found.

6. Empirical analysis

6.1 Knowledge sourcing

The result demonstrates that knowledge sourcing activities within either high- tech or low- tech industry appears a pattern of complementarity (see table 3 and 4). However, the effect of the horizontal linkage on other knowledge sourcing activities is quite different between high- tech and low- tech industries. It has the significant influence on increasing internal R&D and the linkage to customers and suppliers if firms are in high- tech industries, but only significantly affects on the linkage to suppliers and informal resources while firms are in low- tech industries. It shows that firms in high- tech industries collaborate with competitors or other companies are more likely to construct the knowledge flow to connect up- and down- stream in its supply chain and engage more in internal R&D. Compare to high- tech industries, firms in low- tech industries are more likely to access knowledge by informal approaches if they derive knowledge from other companies within supply chain (competitors, customers and suppliers). This reveals that Taiwanese low- tech industries still carry innovation activities inside their organizational boundary and do not build formal channels/contracts to collaborate with others (Chen et al. 2011).

Except the effect from other knowledge linkages, the previous literature has indicated other factors such as firm resources and capabilities, government financial support and exporting, may also influence on the knowledge sourcing activities. In the result of either high- tech or low- tech industry, firm size, measured by the number of employees, shows its positive significant influence on internal R&D with inverted U shape. However, it has the contrary effect on informal knowledge linkage with negative influence (U shape) in high- tech industries but positive impact in low- tech industry (inverted U shape) although non-significant. The interesting point discovered here is medium- size firms in high- tech industries are more likely to engage in internal R&D than to access knowledge in informal approaches. It may be these medium- size firms are in the middle of growth so the resources they have are only enough to their own R&D engagement, but not to share or collaborate with others. Although sharing and collaboration can reduce some risk and cost of R&D investment, firms need to have strong core technology or unsubstitutive characteristics to sustain their own competitiveness.

Employee degree shows the positive impact on both internal and external R&D activities if firms are in high- tech industries, however, what surprises is the higher percentage of employee with degree actually reduce the probability of internal R&D in low- tech industries. The explanation can be either the purpose of recruiting employment with degree for firms in low- tech industries is not to engage in internal R&D, or those employees directly bring in outside technology/technique because low- tech industries are considered as more technology users (Hauknes and Knell 2009).

The descriptive statistics show that more than 60% of firms in high- tech industries received financial support from Government and even higher (72%) in low- tech industries (table 2). Even though lower value of goods produced in low- tech industries, they still play an important role on Taiwanese economy. To develop Taiwanese industries' competitiveness and strength the economy, the Government not only support high- tech industries but also put forward constructive policies to upgrade low- tech industries (Chen et al. 2011). As might be expected, Government financial support is positively associated with competitor and public knowledge sourcing in high- tech industries and with customer knowledge sourcing in low- tech industries. However, the opposite result is found to supplier and informal knowledge in high- tech and low- tech industries. The explanation can be the knowledge firms usually derived from suppliers and exhibitions/industrial associations is more financial related.

6.2 Innovation activities

The result in table 5 shows that high- tech industry has a negative significant effect on the decision of product innovation. This may be affected by the fact of more than 50% of firms in high- tech industries are actually low- tech firms. However, firms with internal R&D activities, the backward and horizontal knowledge linkages are more likely to carry product innovation if they are in high- tech industries. Most notably with regard to the backward knowledge linkage, the negative impact on product innovation for all firms becomes a positive effect for firms in high- tech industries. This result shows that the decision to engage in product innovation for firms in high- tech industries highly relies on the knowledge derived from suppliers. It supports Grimpe and Sofka (2009)'s finding that high- tech industry tends to access suppliers to derive technological knowledge.

No direct significant effect of high- tech industry on product innovation success or process innovation decision was found, but firms with the forward knowledge linkage are less likely to carry on process innovation if they are in high- tech industries. It may be the fact that Taiwanese manufacturing firms in high- tech industries utilised customers' knowledge mainly to product innovation rather than process innovation, and only 30 % of firms in high- tech industries engaged in both product and process innovation (see table 2). Overall, the result matches the assumption that firms in high- tech industries tend to derive knowledge from suppliers for innovation (product innovation) while firms in low- tech industries are more likely to link to customers' knowledge (process innovation). However, opposite result here shows that the competitors' knowledge affects significantly positively on product innovation if firms are in the high-tech industries. The explanation can be Taiwanese innovative manufacturing firms in high- tech industries collaborate more with competitors or other companies to engage in product innovation due to higher risk of the innovation on high- tech products.

Overall, there is a certain knowledge searching strategy to innovation in high-tech and low- tech industries because of different characteristics/demand. However, it has been indicated that there is a kind of special relationship (Guan- Xi) and some informal collaboration between organizations are formed by this kind of private relationship to reduce the risk of uncertainty and share some resources (Gulati 1998). Many Taiwanese companies are family enterprises especially those low- tech industries (called traditional industries in Taiwan). The special 'Guan- Xi' of relationship causes an effect on knowledge sourcing behaviour due to Taiwanese culture and society (Chung 2004).

6.3 Innovation outputs- value added

The result shows that product innovation has a positive significant effect on firm growth (both employment and sales growth). The interaction terms indicate that product innovation has significant positive effect on employment growth if firms are in high-tech industries. The summary statistics in table 2 shows that 62% of firms in high- tech industries engaged in product innovation while 57% of them engaged in process innovation. Compare to firms in low-tech industries, it remains the same percentage of firms with process innovation but only 48% of firms have product innovation. Although higher percentage of firms in high- tech industries with product innovation but the average of a firm's innovation success in high- tech industries is only slightly higher (about 4%) than the one's in low- tech industries. This could be the fact that firms with product innovation if in high- tech industries contrarily caused a non-significant negative impact on sales growth. Moreover, product innovation success does not influence significantly on any firm performance which shows that the growth and productivity of Taiwanese manufacturing firms didn't rely heavily on their innovative products, regardless of the type of industry. Another interesting point is that a firm with process innovation in high- tech industries also causes a non-significant negative effect on employment growth while all firms (in both high- tech and low- tech industries) with process innovation actually has positive significant impact. Compared to high- tech industries, low- tech industries are characterized by more process innovation. Also, it may be the reason high- tech industries did not benefit on its employment growth by doing process innovation. Furthermore, by innovating manufacturing process in high- tech industries, the demand of labor may reduce much more than the increase of R&D employee. Therefore, it causes the negative employment growth. In general, it is sometimes difficult to categorize the effect of innovation on firm performance because of the highly uncertainty in innovation activities. A firm with innovation success can lead to high value added but gain nothing if its innovation fails and it is easy to lose its market share due to the thread from its strong rivals with superior resources and capabilities (Coad and Rao, 2008).

7. Conclusion

The growth of innovation in low- tech industries has brought the research attentions. However, the lack of comparative studies on high- tech and low- tech industries leaves this research gap to be explored. There has been some research showing the different innovation activities between high- tech and low- tech in term of determinants and industrial environment. This study uses the lens of innovation value chain to investigate the difference of knowledge sourcing pattern, innovation activities and outputs. It shows that there are indeed some differences of the whole value added process via innovation between high- tech and low- tech industries.

At the first step of innovation value chain, the model is estimated separately on high- tech and low- tech industries. Complementary relationship has been found between knowledge sourcing activities in both high- tech and low- tech industries. However, different sourcing patterns are found. Firms in high- tech industries with the linkages to competitors or other companies are more likely to construct knowledge flows to connect up- and down- stream in their supply chain and engage more in internal R&D. Comparatively, firms in low- tech industries (called traditional industries in Taiwan) have less formal engagement with external knowledge but interact by informal paths such as exhibition or industrial associations. The result also indicates an interesting point that a firm in low- tech industries reduces its internal R&D engagement if it hires

The second step of innovation highlights the important knowledge linkages, internal firms' resources and capabilities and other factors which contribute to innovation. The result reflects that firms in high- tech industries collaborate more with their suppliers and competitors for product innovation to complement their internal R&D knowledge. Moreover, firms in low- tech industries derive knowledge from their customers for process innovation although no direct significant contribution shown in the result. The most surprising point here is firms in high- tech industries are actually less likely to engage in product innovation.

The last step of innovation process connects to firm performance to measure the value added. The result shows only the difference of product innovation effect on employment growth when firms are in high- tech industries. Innovation is an unpredictable activity and contains uncertainty. Because there is no assurance of innovation, a firm may either apply innovation successfully to commercial end or waste the entire investment when something goes wrong (with bad luck or wrong decision/strategy). Therefore, it is sometimes hard to conclude a significant effect of innovation on firm performance especially with the cross sectional data.

Table 1 The classification of Taiwanese manufacturing industries

Industry	Description	Amount
Low- tech	Non-metallic mineral and quarrying	40
	Food, beverages and tobacco	75
	textiles, wearing apparel, leather, paper and printing	218
	Natural resources (petroleum, coal, rubber, plastic and wood) manufacturing	93
	Basic and fabricated metal	246
	Machinery repair and installation, energy supply, and wastewater and pollution remediation	20
	Construction	156
	Others	48
High- tech	Chemical material and products, medical goods	131
	Electronic Parts and Components Manufacturing	244
	Computers, Electronic and Optic Products Manufacturing	162
	Electrical Equipment Manufacturing	102
	machinery and transportation equipment	271

Table 2 Summary Statistics of high- tech and low- tech industries

		High-tech industries (910)			Low-tech industries (896)		
Variable description	**T test**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**N**
Innovation indicators							
Product innovation success (%)	V	61.07	29.77	645	57.20	31.65	613
Product innovation (0/1)	V	0.62	0.49	910	0.48	0.50	896
Process innovation (0/1)	X	0.57	0.50	910	0.57	0.50	896
Product and process innovation (0/1)	V	0.30	0.46	910	0.24	0.43	896
Knowledge sourcing activities							
Internal R&D (0/1)	V	0.85	0.36	910	0.79	0.41	896
Percentage Internal R&D (%)	X	27.55	25.74	831	30.15	29.43	688
External R&D (0/1)	X	0.32	0.47	910	0.28	0.45	896
Percentage External R&D (%)	X	8.96	18.52	831	7.88	17.81	688
Forward knowledge (0/1)	X	0.74	0.44	910	0.72	0.45	896
Backward knowledge (0/1)	V	0.70	0.46	910	0.55	0.50	896
Horizontal knowledge (0/1)	V	0.63	0.48	910	0.56	0.50	896
Public knowledge (0/1)	V	0.56	0.50	910	0.39	0.49	896
Informal knowledge (0/1)	V	0.71	0.45	910	0.55	0.50	896
Internal resources							
Firm size (employee number)	V	270.28	824.59	910	132.30	436.35	896
Subsidiary (0/1)	X	0.16	0.37	910	0.17	0.37	896
Firm age (0/1, 0= three years or more, 1= less than three years)	X	0.05	0.22	910	0.07	0.25	896
Firm capability							
Employee degree (%)	X	47.95	27.35	862	46.78	30.49	822
Training (0/1)	V	0.81	0.39	910	0.68	0.47	896
Government assistance							
Financial support (0/1)	V	0.62	0.49	864	0.72	0.45	711
Market strategy							
Export (0/1)	V	0.75	0.44	910	0.57	0.50	896

Note: T test is for the significant difference of each variable between high- tech and low- tech industries. ‘x’ means no significant difference; ‘v’ means significant difference.

Table 3 Knowledge sourcing_ high tech industry

Variables	Internal R&D	External R&D	Forward knowledge	Backward knowledge	Horizontal knowledge	Public knowledge	Informal knowledge
Knowledge sources							
Internal R&D	-	0.096** (0.047)	-0.015 (0.046)	0.030 (0.048)	0.133** (0.054)	0.046 (0.063)	0.071 (0.047)
External R&D	0.036* (0.020)	-	0.025 (0.032)	0.001 (0.035)	0.022 (0.038)	0.095** (0.044)	-0.030 (0.032)
Forward knowledge	0.0003 (0.023)	0.032 (0.037)	-	0.041 (0.038)	0.171*** (0.042)	0.034 (0.048)	0.012 (0.033)
Backward knowledge	0.009 (0.022)	0.011 (0.040)	0.036 (0.037)	-	0.350*** (0.039)	0.138*** (0.050)	0.068* (0.035)
Horizontal knowledge	0.052** (0.022)	0.018 (0.036)	0.144* (0.035)	0.300*** (0.034)	-	-0.009 (0.047)	0.045 (0.033)
Public knowledge	0.016 (0 .025)	0.084** (0.043)	0.026 (0.039)	0.116*** (0.042)	0.0002 (0.046)	-	0.502*** (0.033)
Informal knowledge	0.048 (0.030)	-0.031 (0.049)	0.019 (0.043)	0.086* (0.047)	0.055 (0.052)	0.657*** (0.028)	-
Resource indicators							
Employment	0.0002*** (0.0001)	-0.00003 (0.00004)	0.00002 (0.00004)	0.00003 (0.00004)	0.00002 (0.00004)	0.00006 (0.00006)	-0.0001** (0.0001)
Employment-squared	$-1.12x10^{-08}$*** (0.000)	$4.60x10^{-09}$ (0.000)	$-3.78x10^{-10}$ (0.000)	$-7.34x10^{-10}$ (0.000)	$-2.84x10^{-11}$ (0.000)	$-2.49x10^{-09}$ (0.000)	$4.84x10^{-08}$** (0.000)
Firm age	0.042 (0.031)	0.089 (0.078)	0.083 (0.058)	0.061 (0.063)	-0.165** (0.079)	-0.016 (0.084)	0.031 (0.054)
Subsidiary	-0.011 (0.031)	-0.017 (0.047)	-0.017 (0.045)	-0.051 (0.049)	-0.011 (0.050)	0.011 (0.061)	-0.021 (0.043)
Capability indicators							
Employee degree	0.001* (0.0004)	0.001** (0.001)	-0.001 (0.0006)	0.00002 (0.0006)	0.0006 (0.0007)	0.0004 (0.0008)	0.0001 (0.001)
Employee training	0.060** (0.030)	0.046 (0.042)	0.022 (0.041)	0.108** (0.044)	-0.021 (0.045(	0.0003 (0.054)	0.043 (0.039)
Government financial support	-0.016 (0.021)	0.051 (0.035)	-0.034 (0.032)	-0.134*** (0.032)	0.068* (0.038)	0.117*** (0.043)	-0.096*** (0.028)
Export	0.060** (0.029)	0.030 (0.040)	0.056 (0.039)	0.027 (0.041)	0.012 (0.045)	0.014 (0.051)	0.014 (0.035)
Observations	825	825	825	825	825	825	825
Log likelihood	-286.741	-506.112	-453.384	-417.618	-479.517	-388.368	-306.840

Note: Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. All the figures in the table are marginal effects generated from probit models. All models include industry dummies.

Firm age: A firm was established after 1st January 2004. 0: established more than 3 years; 1: establish less than 3 years.

Table 4 Knowledge sourcing_ low tech industry

Variables	Internal R&D	External R&D	Forward knowledge	Backward knowledge	Horizontal knowledge	Public knowledge	Informal knowledge
Knowledge sources							
Internal R&D	-	0.142*** (0.042)	-0.042 (0.044)	0.046 (0.058)	0.022 (0.053)	-0.013 (0.058)	-0.018 (0.059)
External R&D	0.089*** (0.027)	-	0.050 (0.038)	0.032 (0.047)	0.072 (0.045)	0.083* (0.048)	-0.026 (0.053)
Forward knowledge	-0.027 (0.029)	0.053 (0.039)	-	0.002 (0.047)	0.037 (0.046)	-0.029 (0.051)	0.144*** (0.052)
Backward knowledge	0.021 (0.032)	0.025 (0.040)	-0.0003 (0.039)	-	0.148*** (0.043)	0.060 (0.047)	0.235*** (0.046)
Horizontal knowledge	0.009 (0.028)	0.060 (0.037)	0.028 (0.037)	0.146*** (0.041)	-	0.017 (0.045)	0.112** (0.047)
Public knowledge	-0.013 (0.034)	0.080* (0.044)	-0.015 (0.045)	0.064 (0.051)	0.022 (0.050)	-	0.542*** (0.034)
Informal knowledge	-0.019 (0.035)	-0.030 (0.047)	0.116** (0.046)	0.250*** (0.048)	0.117** (0.051)	0.541*** (0.034)	-
Resource indicators							
Employment	0.0005*** (0.0002)	-0.00004 (0.0001)	0.0002* (0.0001)	0.0003 (0.0002)	0.0004*** (0.0002)	-0.00008 (0.0001)	0.0002 (0.0002)
Employment-squared	$-6.87\text{x}10^{-08}$** (0.000)	$1.49\text{x}10^{-08}$ (0.000)	$-4.62\text{x}10^{-08}$** (0.000)	$-4.53\text{x}10^{-08}$ (0.000)	$-7.65\text{x}10^{-08}$** (0.000)	$5.35\text{x}10^{-09}$ (0.000)	$-3.12\text{x}10^{-08}$ (0.000)
Firm age	0.064 (0.040)	0.077 (0.078)	0.026 (0.065)	0.017 (0.081)	-0.119 (0.076)	-0.100 (0.082)	-0.0002 (0.087)
Subsidiary	0.015 (0.041)	-0.099** (0.046)	-0.030 (0.055)	0.047 (0.062)	0.029 (0.060)	0.088 (0.061)	-0.044 (0.062)
Capability indicators							
Employee degree	-0.0009** (0.0005)	0.0005 (0.0006)	-0.0002 (0.0006)	0.0008 (0.0007)	0.0004 (0.0007)	0.0003 (0.0007)	0.0001 (0.0008)
Employee training	0.163*** (0.037)	0.088** (0.040)	0.046 (0.041)	0.013 (0.048)	0.080* (0.046)	0.006 (0.050)	0.061 (0.052)
Government financial support	0.042 (0.036)	0.011 (0.041)	0.074* (0.043)	-0.125*** (0.045)	-0.034 (0.047)	-0.027 (0.049)	-0.119** (0.049)
Export	0.072** (0.032)	0.007 (0.039)	0.027 (0.039)	0.002 (0.044)	-0.004 (0.043)	0.076* (0.046)	-0.017 (0.049)
Observations	667	667	660	667	667	667	667
Log likelihood	-279.951	-379.265	-370.958	-393.263	-418.821	-319.337	-300.018

Note: Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1. All the figures in the table are marginal effects generated from probit models. All models include industry dummies.

Firm age: A firm was established after 1st January 2004. 0: established more than 3 years; 1: establish less than 3 years.

Table 5 Innovation production_ high- tech industry effect

Variables	**Product innovation: decision**	**Product innovation: success**	**Process innovation: decision**
Knowledge sourcing			
Internal R&D (0/1)	0.0004 (0.0005)	0.153*** (0.051)	0.0004 (0.0005)
External R&D (0/1)	0.0002 (0.0009)	0.045 (0.082)	0.001 (0.0009)
Forward (0/1)	-0.031 (0.042)	-2.316 (4.013)	0.048 (0.044)
Backward (0/1)	-0.067* (0.041)	1.880 (3.593)	0.037 (0.043)
Horizontal (0/1)	-0.037 (0.039)	-6.059* (3.625)	-0.00004 (0.041)
Public (0/1)	0.014 ()0.047	-7.090* (4.262)	0.042 (0.047)
Informal (0/1)	0.013 (0.048)	3.798 (4.196)	-0.120** (0.047)
KS*High- tech Industry			
InterRD*HD	0.157*** (0.053)	-6.986 (5.649)	-0.014 (0.055)
ExterRD*HD	0.015 (0.044)	4.621 (3.854)	0.034 (0.043)
Forward*HD	0.015 (0.059)	-2.011 (5.349)	-0.099* (0.060)
Backward*HD	0.117** (0.056)	-5.859 (5.142)	-0.015 (0.059)
Horozontal*HD	0.102* (0.053)	2.936 (4.985)	-0.030 (0.057)
Public*HD	-0.076 (0.066)	4.609 (5.669)	0.026 (0.064)
Informal*HD	-0.002 (0.069)	2.849 (5.931)	0.073 (0.068)
Resource indicators			
Employment	0.0002*** (0.00007)	-0.003 (0.005)	0.00007 (0.00006)
Employment-sq	$-2.69\text{x}10^{-08}$* (0.000)	$9.21\text{x}10^{-08}$ (0.000)	$3.84\text{x}10^{-09}$ (0.000)
Firm age	0.077 (0.049)	-1.707 (4.652)	-0.033 (0.055)
Subsidiary	-0.003 (0.038)	-0.009 (3.220)	-0.022 (0.038)
Capability indicators			
Employee degree	0.003*** (0.0005)	0.014 (0.042)	-0.0005 (0.0005)
Employee training	0.087** (0.034)	4.031 (3.208)	0.0009 (0.034)
Government financial support	0.009 (0.029)	1.394 (2.483)	0.030 (0.029)
Export	0.031 (0.030)	5.999** (2.692)	-0.006 (0.030)
High- tech industry (0/1)	-0.221*** (0.073)	11.979 (7.584)	0.023 (0.078)
Observations	1447	996	1447
Log likelihood	-899.020	-4331.7811	-958.6446

Note: Standard errors in parentheses; *** p<0.01, **p<0.05, *p<0.1. All the figures in the table are marginal effects generated from Probit/Tobit models.

Firm age: A firm was established after 1st January 2004. 0: established more than 3 years; 1: establish less than 3 years.

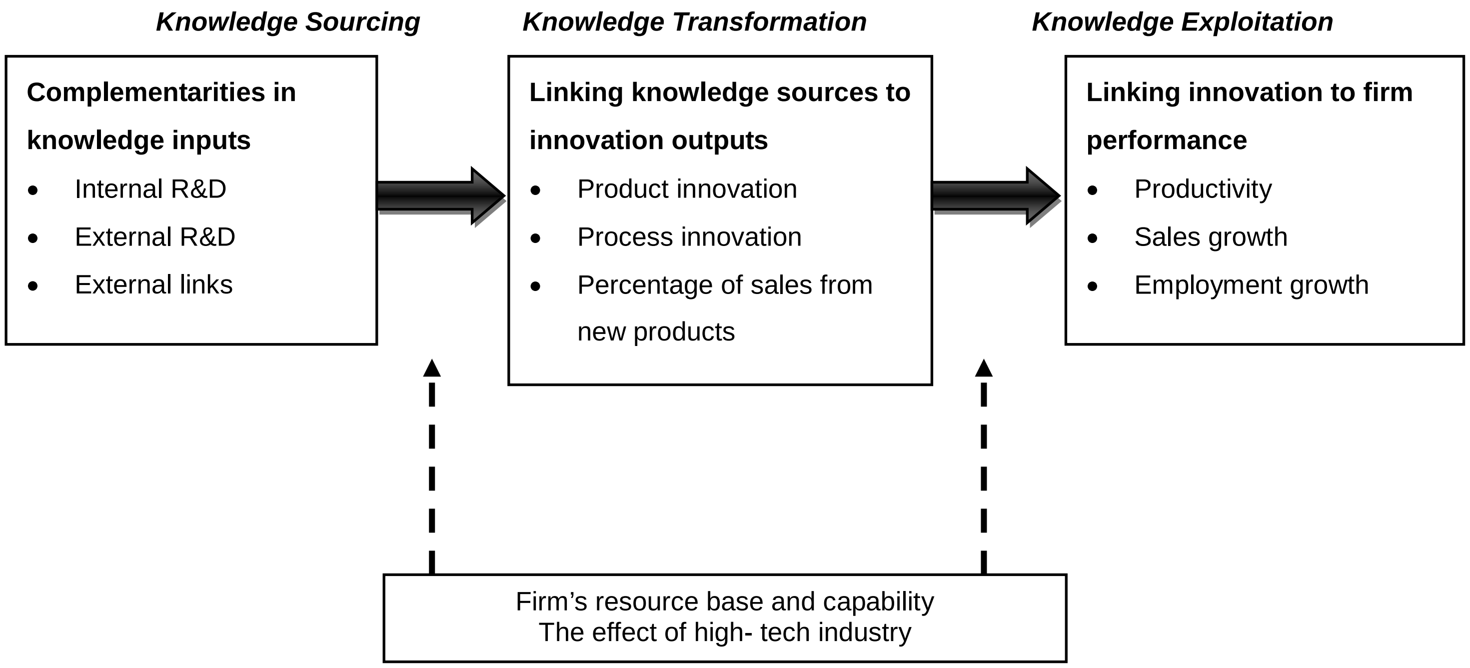
Table 6 Performance estimations_ high- tech industry effect

Variables	Product innovation decision indicators			Product innovation success indicator		
	Employment growth	**Sales growth**	**Productivity**	**Employment growth**	**Sales growth**	**Productivity**
Constant	-0.167 (0.081)	8.881 (5.526)	157077 (100381.6)	-0.214 (0.142)	14.687* (8.632)	306742.1 (233299.3)
Innovation activities						
Product innovation	0.099** (0.046)	3.515* (2.121)	32604.22 (34511.81)	0.0004 (0.001)	0.014 (0.043)	-1979.939 (1638.231)
Process innovation	0.105** (0.047)	-3.297 (3.166)	-57346.75 (50101.29)	0.151** (0.062)	-4.918 (4.212)	-50223.63 (57494.04)
Innovation*H- tech industry						
Product inno_ HD	0.207* (0.106)	-2.626 (1.668)	-2794.23 (28805.19)	-0.003 (0.002)	-0.008 (0.044)	2041.002 (1817.049)
Process inno_ HD	-0.020 (0.123)	3.446 (3.359)	2877.26 (58526.2)	0.002 (0.160)	5.359 (4.522)	-24127.28 (65700.14)
High- tech industry	-0.073 (0.104)	-3.156 (2.235)	18615.22 (49935.18)	0.266 (0.207)	-5.350 (3.985)	-73047.47 (157034.2)
Resource indicators						
Employment	-0.0004** (0.0002)	-0.001*** (0.0005)	-44.784*** (13.246)	-0.0004* (0.0002)	-0.001** (0.0007)	-104.301*** (34.862)
Employment-squared	6.77×10^{-08}*** (2.34×10^{-08})	2.61×10^{-07}*** (9.89×10^{-08})	0.002*** (0.0008)	6.80×10^{-08}*(4.05×10^{-08})	3.34×10^{-07} (2.05×10^{-07})	0.021*** (0.008)
Firm age	-0.062 (0.068)	7.317 (7.948)	17472.73 (59110.71)	-0.111 (0.093)	10.923 (1.462)	34866.59 (81021.47)
Subsidiary	0.388* (0.211)	-1.365 (0.967)	-39210.98** (15838.91)	0.552* (0.291)	-2.118 (1.462)	-50189.81** (23219.88)
Capacity indicators						
Employee degree	0.0006 (0.0005)	-0.056 (0.041)	-511.530 (693.270)	0.001** (0.0006)	-0.083 (0.060)	-618.283 (1002.491)
Employee training	0.027 (0.048)	-1.194 (2.081)	-13508.66 (28284.74)	0.051 (0.073)	-1.328 (3.147)	-2648.419 (49944.89)
Government financial support	-0.046 (0.070)	-0.754 (1.705)	-11997.79 (33176.07)	0.0008 (0.097)	-1.503 (2.737)	-28943.66 (48429.22)
Export	-0.014 (0.047)	-2.346 (1.777)	-60673.3 (37305.63)	0.014 (0.063)	-4.100 (2.800)	-70310.25 (50427.93)
Observations	1492	1492	1492	1027	1027	1027

Note: Standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Firm age: A firm was established after 1st January 2004. 0: established more than 3 years; 1: establish less than 3 years.

Figure 1 The Innovation Value Chain: structure and key indicators



References

Cassiman, B. and Veugelers, R. (2002). R&D cooperation and spillovers: some empirical evidence from Belgium. American Economic Review, Vol. 92, pp. 1169-1184.

Chesbrough, H. (2003). Open Innovation: The New Imperative For Creating And Profiting From Technology. Boston, Massachusetts: Harvard Business School Press.

Chesbrough, H. (2006). Open Innovation: a new paradigm for understanding industrial innovation. In Open Innovation: researching a new paradigm. H. Chesbrough, W. Vanhaverbeke and J. West (Eds.). Oxford University Press, pp. 1-12.

Chung Y. (2004) Organizational Capabilities, Embeddedness, Network Linkages And Performance: A Study on Taiwan E-Commerce Ventures. Master dissertation

Coad A. and Rao R. (2008) Innovation and firm growth in high- tech sectors: A quantile regression approach. Research policy, Vol. 37 (4), pp. 633- 648

Cohen, W. and Levinthal, D. (1990). Absorptive Capacity: A New Perspective On Learning And Innovation. Administrative Science Quarterly, Vol. 35(1), pp. 128-152.

Crépon, B. Duguet, E., and Mairesse, J. (1998). Research, Innovation and Productivity: An econometric analysis at the firm level. Economics of Inovation and New Technology Vol. 7, pp. 115-158.

Del Barrio-Castro, T. and Garcia-Quevedo, J. (2005). Effects of university research on the geography of innovation. Regional Studies Vol. 39 (9), pp. 1217-1229.

Freeman, C. and Soete, L. (1997). The Economics of Industrial Innovation 3rd ed. The MIT Press, Cambridge Massachusetts.

Ganotakis P. and Love J. (forthcoming) The innovation value chain in new technology based firms, Journal of Product Innovation Management.

Geroski, P. Machin, S., and Van Reenen, J. (1993). The Profitability of Innovating

Firms. RAND Journal of Economics, Vol. 24, pp. 198-211.

Greene, W.H. (2005). Econometric Analysis (5th ed.). New Jersey: Prentice-Hall.

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

Harris, R.I.D. and Trainor, T. (1995). Innovation and R&D in Northern Ireland Manufacuring: A Schumpeterian Approach. Regional Studies, Vol. 29, pp. 593-604.

Hauknes J. and Knell M. (2009) Embodied knowledge and sectoral linkages: An input-output approach to the interaction of high- and low- tech industries. Research policy, Vol. 38 (3), pp. 459- 469

Hemphill, T.A. (2003). Cooperative Strategy, Technology Innovation and Product Development in Industrial Companies. International Journal of Production Economics, Vol. 69, pp. 169-76.

Harris R. and Li Q. (2009). Exporting, R&D, and absorptive capacity in UK establishments. Oxford Economic Papers, Vol. 61, pp. 74-103.

Horn, P. M. (2005). The changing nature of innovation. Research Technology Management, Vol. 48, pp. 28-33.

Joshi, A.W. and Sharma, S. (2004). Customer Knowledge Development: Antecedents and Impact on New Product Performance. Journal of Marketing, Vol. 68, pp. 47-59.

Link, A.N., Paton, D., and Siegel, D.S. (2005). An Econometric Analysis of Trends in Research Joint Venture Activty. Managerial and Decision Economics 26: 149-158.

Lööf, H. and Heshmati, A. (2002). Knowledge capital and performance heterogeneity: A firm level innovation study. International Journal of Production Economics, Vol. 76, pp. 61-85.

Love, J. H. and Ganotakis P. (2010). LEARNING BY EXPORTING: LESSONS FROM HIGH-TECHNOLOGY SMES. Paper presented at DRUID Summer

Conference, Imperial College London Business School.

Love, J. H. and Mansury M. (2007). External Linkages, R&D and Innovation Performance in US Business Services. Industry and Innovation, Vol. 14, pp. 477-496.

Love J.H. and Roper, S. (1999). The determinants of innovation: R & D, technology transfer and networking effects. Review of Industrial Organization, Vol. 15, pp. 43-64.

Love, J.H. and Roper, S. (2001). Location and network effects on innovation success: evidence for UK, German and Irish manufacturing plants. Research Policy, Vol. 30, pp. 643-661.

Love, J.H., Roper, S., and Hewitt-Dundas, N. (2010). Service Innovation, Embeddedness and Business Performance: Evidence from Northern Ireland. Regional Studies, Vol. 44, pp. 983-1004.

McDonald, J. and Moffitt, R. (1980). The uses of Tobit Analysis. The Review of Economics and Statistics, Vol. 62(2), pp. 318-321.

Roper S. and Arvanitis S. (2009). From Knowledge to Added Value: A comparative, panel-data analysis of the Innovation Value Chain in Irish and Swiss Manufacturing Firms. Paper presented at DRUID Summer Conference, Copenhagen.

Roper, S., Du, J., and Love, J. H. (2006). Knowledge sourcing and innovation. Aston Business School Research Paper 0605. Birmingham.

Roper, S., Du, J., and Love, J. H. (2008). Modelling the innovation value chain. Research Policy, Vol. 37, pp. 961-977.

Roper S. and Love J. H. (2002). Innovation and export performance: evidence from the UK and German manufacturing plants. Research Policy, Vol. 31(7), pp. 1087-1103.

Roper, S. and Hewitt-Dundas, N. (2005). Measuring the Impact of Grant Support for Innovation: Panel Data Evidence for Irish Firms. European Regional Science Association, Amsterdam, (August 2005).

Roper, S., Hewitt-Dundas, N., and Love, J.H. (2004). An Ex Ante Evaluation Framework for the Regional Benefits of Publicly Supported R&D Projects. Research Policy, Vol. 33,pp. 487-509.

Roper, S. and Love, J.H. (2005). Innovation Success and Business Performance - An All-Island Analysis. All Island Business Model Research Report, Inter Trade Ireland, July 2005.

Schmidt, T. (2010). Absorptive Capacity – One Size Fits All? A Firm-level Analysis of Absorptive Capacity for Different Kinds of Knowledge. Managerial and Decision Economics, Vol. 31(1) pp. 1-18.

Shelanski, H.A. and Klein, P.G. (1995). Empirical research in transaction cost economics: a review and assessment. Journal of Law, Economics and Organization, Vol. 11, pp. 335-361.

Smith, D.J. and Tranfield, D. (2005). Talented suppliers? Strategic change and innovation in the UK aerospace industry. R&D Management, Vo. 35, pp. 37-49.

Veugelers, R. and Cassiman, B. (1999). Make and buy in innovation strtegies: evidence from Belgian manufacturing firms. Research Policy, Vol. 28, pp. 63-80.