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Cross Sectoral Differences in Drivers of Innovation

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Cross Sectoral Differences in the Drivers of Innovation: Evidence from the Irish Community Innovation Survey

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Abstract

This paper analyses differences across sectors in firms' propensity to innovate and the relative importance of inputs to innovation classifying firms into four broad sectors. The propensity and drivers of four types of innovation (new to firm, new to market, process and organisational) within these sectors are then analysed. The results indicate that, for new to firm and new to market innovation, there is a strong degree of heterogeneity in the drivers of innovation across sectors. The propensity to introduce process or organisational innovations varies slightly across sectors but that there is no evidence of differences across sectors in the drivers of innovation. These results have important implications for policy instruments to meet the needs of targeted firms.

Keywords: Innovation, Sectoral Differences, Knowledge Sourcing
JEL Codes: O31, C50, L50

1. Introduction

This paper analyses sectoral differences in the propensity to innovate and the extent to which the mechanisms through which firms innovate vary across sectors. This is accomplished through the use of the Irish Community Innovation Survey (CIS) 2004-06. Four broad sectoral classifications are identified; high-technology manufacturing, all other manufacturing (AOM), wholesale, transport, storage and communication (WTS&C) and financial intermediaries (FI). Peneder (2010) alludes to a tension between firm-level and sector-level studies of innovation activity. He notes that the former point to heterogeneity of behaviour among individual firms while the latter show significant differences between sectors and observed consistencies in sectoral data. This tension, he argues, has important implications for innovation policy in that "industry characteristics matter and cannot be ignored [and] their accurate understanding helps to design policy programs and tailor them more effectively to the needs of targeted firms" (Peneder 2010: 324).

It has become standard in the literature to control for sector specific effects in the innovation production function framework. Roper et al. (2008), Freel (2003), Love and Roper (2002) and Oerlemans et al. (1998) Love and Roper (2002)all control for sectoral differences in the propensity for firms to engage in innovation. Doran and O'Leary (2011) and Hall et al. (2009) provide evidence of heterogeneity across sectoral classifications in the propensity to innovate; suggesting that high-technology firms have a higher likelihood of engaging in certain forms of innovation. These studies essentially control for variation in the intercept coefficient by including a series of dummy variables in the innovation production function; thereby faciliting an analysis of differences in innovation propensity across sectors.

However, there has been relatively little discussion or analysis of the variation in the mechanisms through which firms in different sectors generate innovation output. In essence, while it is standard to control for differing propensities to innovate, no such consideration is granted to potential variation in the importance of innovation inputs across sectors. This paper aims to address this defficiency in the literature by utilising econometric techniques to assess whether input coefficients in the innovation production function are stable or whether they vary depending on the sector in which the firm operates.

This paper identifies four distinct types of innovation; new to market (NtM) and new to firm (NtF) product innovation, process innovation and organisational innovation. These four types of innovation are consistent with Schumpeter's (1934) and the OECD's (2005) distinction between different forms of innovation output.

Innovation production functions are estimated using probit models incorporating intercept dummy variables to test for differing propensities to innovate across sectors. Subsequently sectoral restriced models are estimated and likelihood-ratio tests utilised to test for stability in the coefficient estimates across sectors; thereby facilitating an analysis of whether the innovation activity of firms vary among sectors.

The remainder of the paper is structured as follows. Section 2 presents a review of the relevent literature and places the contributions of this paper within this literature. Following this, Section 3 outline the methodology employed by this paper. The data utilised by this paper is then summarized in Section 4. Section 5 presents the empirical results derived and a discussion of the key findings from these results. The final section concludes and provides policy implications derived from the evidence presented in Section 5.

2. Literature Review

Howells (2002) and Lissoni (2001) argue that innovation is of vital importance, not only for business success, but also for economic growth and social wellbeing. This paper, in analysing whether the determinants of innovation vary across sectors, aims to provide an insight into whether targeted policy formation is required to ensure that firms in differing sectors receive the necessary support in their innovation activities.

In this section, conceptual frameworks and empirical evidence on the drivers of business-level innovation are presented, followed by a discussion on why the relative importance of these drivers may vary across sectors.

It is clear from the literature that business innovation is conditioned by internal and external knowledge generation activities, with complentarity between both. The importance of internal sources of knowledge is highlighted by Kline and Rosenberg

(1986), who emphasize the sourcing of knowledge inside the business through the performance of R&D, which involves solving “problems all along the chain of innovation from the initial design to the finished production processes” (1986:303). This performance of internal R&D activity is viewed as a crucial component in firms’ innovation production as it allows firms to expand their knowledge base (Griliches 1992; Freel 2003).

Interaction with external agents may also act as an important source of knowledge for innovative firms. Lundvall (1988), Kline and Rosenberg (1986) and Nonaka et al. (2001), when viewing interactive learning as a positive source of knowledge, suggest that external linkages can be exploited for the advancement of business innovation. For firms to innovate they utilise, combine and transform existing knowledge into a new product or process. However, internal knowledge is often not sufficient and acquiring new knowledge from outside the organisation is frequently required (Howells 2002). Bathelt et al. (2004) suggest that firms engage in external knowledge sourcing to complement their existing knowledge or to overcome deficiencies in their internal knowledge. Similarly, Romijin and Albu (2002) and Gertler and Levitte (2005) note that external networking and interaction may be viewed as an important source of knowledge for innovation, with firms learning through interaction. Cohen and Levinthal (1989) emphasise the importance of R&D as a direct source of knowledge for innovation and for developing absorptive capacity which enables businesses to identify, evaluate and exploit external sources of knowledge.

This interaction may take place with market-based agents such as customers and suppliers or non-market-based agents such as higher education institutes or public research facilities. The form of interaction may range from contractual collaboration with an agent to social or informal, perhaps unintentional, networking. For the purposes of this paper interaction is defined in the Irish CIS as active participation with other enterprises or non-commercial institutions on innovation activities, where both parties do not need to benefit commercially (Central Statistics Office 2009).

Apart from internal knowledge generation and external linkages a number of firm specific factors may also affect innovation performance. Whether the firm is indigenous or foreign owned may play a role in explaining innovation performance, which is an issue of particular relevance to Ireland given its reliance on foreign direct investment (Klomp and Van Leeuwen 2001; Jordan and O'Leary 2008; Roper et al. 2008). Also, the size of the firm may impact on its innovation performance (Cohen and Klepper 1996).

Of interest in this paper is the extent to which there are sectoral differences in the importance of various determinants of innovation. Kline and Rosenberg (1986) argue that recognition is needed that there are many "black boxes" through which firms' generate differing forms of innovation and that the mechanism through which these innovations arise may vary depending on the type of innovation and the nature of the innovating firm. This suggests that there is a need to consider that innovation activities may vary depending on the sectoral environment a firm operates in.

Sectoral differences has been an important empirical consideration since, at least, Pavitt (1984) identifies a taxonomy of four categories of firm, science-based, specialised suppliers, supplier-dominated and scale-intensive firms, based on sources and patterns of technological change. According to de Jong and Marsili (2006: 216) these sources and patterns "shape and differentiate the pattern of innovation of firms across sectors".

Malerba (2002), in promoting a sectoral system of innovation perspective, argues that that sectors differ greatly in their knowledge bases, technologies, production processes, complementarities, demand, non-firm organizations and institutions. Indeed, Malerba (2004) notes that innovation activity takes place in substantially differentiated sectoral environments; identifying that the sources of knowledge available to firms, the actors involved in the innovation process and the institutions available to firms varies across sectors. Montobbio (2004) notes that empirical analysis can provide stylised facts regarding how innovation activities vary across different sectors.

An example of how the relative importance of different sources of external knowledge may differ across sectors is provided by Schartinger et al. (2002), who consider the nature of industry-university linkages. They find in a study of Austrian businesses and universities that "sectors of economic activity and fields of science engage in different types of interactions" (Schartinger et al, 2002:235). They argue that the variety of industrial sectoral patterns should inform policy in relation to industry-university knowledge interaction.

Sectoral considerations for innovation studies have also emerged from literatures in regional science. Porter's clusters and Marshall's localisation economies have stressed the role of geographical concentration of related and supported industries as a source of innovation. The complementarity of sectoral and spatial influences on business-level innovation is explored by Anselin et al. (2000) who find empirical evidence for the existence of both sectoral and regional differences in the innovative process. Studies of the effects on individual businesses of geographical concentration with others in the same sector has also demonstrated sectoral effects [for example, Bönte (2004) and Görg and Ruane (2001)].

Analyses by Doran and O'Leary (2011) and Hall (2009) identify differing propensities for firms in various sectors to innovate. However, they do not assess whether the driver of innovation vary across sectors. This paper moves beyond the traditional method of controlling for sectoral factors using dummy variables. The method is presented in detail in the next section.

3. Methodology

In order to analyse the effects of various innovation inputs and company specific factors on the innovation performance of firms this paper employs an innovation production function (Oerlemans et al. 1998; Roper 2001; Love and Mansury 2007). Following from Freel (2003), Mansury and Love (2008) and Hall et al. (2009) the innovation production function specified in equation (1) relates the probability of a firm engaging in innovation activity to a number of key explanatory factors. A series of probit models are used to estimate equation (1).

$$IO_i = \alpha_0 + \beta_k EI_{ki} + \chi R \,\&\, D_i + \delta_m Z_{mi} + \phi_n S_{ni} + \varepsilon_i \qquad (1)$$

Where IO_i is a binary indicator of whether firm *i* engaged in one of four forms of innovation considered; new to firm (NtF), new to market (NtM), process or organisation innovation. These varying forms of innovation are considered as it can be expected that each of these types of innovation are the result of a differing combination of innovation inputs. Further to this, the propensity for firms across different sectors to engage in each type of innovation may vary (OECD 2005). Therefore, in order to fully address the variation in innovation output and behaviour across sectors, it is important to analyse the unique process through which firms decide to engage in each form of innovation.

EI_{ki} is a binary indicator of whether firm *i* interacted with external knowledge source *k*. Previous research has shown that external knowledge sources can play an important role in the innovation process of firms (Oerlemans et al. 1998; Freel 2003). However, the nature of the importance of external interaction agents may vary across different types of innovation (Roper et al. 2008; Roper et al. 2010). Therefore, while it is postulated that β_k will have a positive effect on the likelihood of innovating it is highly probably that the importance of the various external agents will vary depending on the type of innovation considered.

It is also widely held in the literature that R&D has a strong positive impact on innovation performance (Cohen and Klepper 1996). Therefore, this paper includes $R\&D_i$; a binary indicator of whether firm *i* engaged in R&D activity during the reference period. Again it is expected that R&D will have a positive impact on the probability of innovation, but that its importance may vary across the different types of innovation. Z_{mi} is a vector of company specific factors including the size of the firm and whether the firm is indigenous or foreign owned.

Finally, S_{ni} is a series of binary variables indicating the sector in which the firm operates. Four sectors are identified by this paper; (i) high-tech manufacturing, (ii) all other manufacturing, (iii) wholesale, transport, storage and communication and (iv) financial intermediaries. High-tech manufacturing is used as the base category. A series of three dummy variables indicates each of the remaining sectors is included.

As the key focus of this paper is to analyse sectoral difference in the innovation performance of Irish firms, equation (1) is initially estimated and special consideration is given to the S_{ni} variables. In doing so this paper identifies the differences among sectors regarding their propensity to engage in each of the three types of innovation activity. However, this paper further develops upon this sectoral analysis by acknowledging that while firms in different sectors may have differing propensities to innovation they may also innovate differently. For example, firms in the high-tech sector and wholesale, transport, storage and communication sector may both introduce organisation innovation, but the mechanisms through which they develop this innovation may differ substantially.

In order to investigate whether this is the case, equation (2) is estimated for each of the individual sectoral classifications used by this paper.

$$IO_{is} = \alpha_{0s} + \beta_{ks} EI_{ki} + \chi_s R \& D_i + \delta_{ms} Z_{mi} + \varepsilon_{is} \qquad (2)$$

Where each variable is defined as above with the addition of the subscript s; here s indicates that, for each sector, different coefficients may be observed. As four sectors are identified in this paper, equation (2) is estimated four times, once for each sector, for each of the four types of innovation. By allowing for a variation in the coefficients across sectors, differences in firms' innovation strategies and value chain can be observed.

In order to ensure that the variance in coefficients across sectors is significantly different, likelihood-ratio tests are employed (Long and Freese 2001; Greene 2008). These involve comparing the restricted estimation of equation (1), for all sectors, to the unrestricted estimations of equation (2), the individual sectoral estimations. The test assesses whether the composite models, comprised of the sectoral estimations of equation (2), provide a better estimation than the aggregate model specified in equation (1). The null hypothesis of the test is that the aggregate model applies to each of the sectors analysed and that there is parameter stability across sectors. This is expressed as:

$$\log L(\hat{\theta}) = \sum_{j=1}^{k} \log L_j(\hat{\theta}_j) \qquad (3)$$

Which states that the sum of the log likelihood of the composite sectoral models equals the log likelihood of the aggregate model. Should the likelihood-ratio test indicate a significant difference in the coefficient estimates across the sectoral regressions this would support the hypothesis that the mechanisms through which firms in different sectors perform innovation vary. While if the likelihood-ratio tests indicate that there is no significant differences across the estimations this suggests that firms, regardless of the industry they operate in, innovate in the same way.

The method used in this paper has advantages over the use of interaction variables as it avoids the problems of potential multicollinearity among the interaction terms while also facilitating an overall statistical test of parameter stability. This would result in 24 additional variables being included in the model which are all products of existing variables, thus raising the likelihood of multicollinearity being observed and incorrect inferences being drawn from the data. The use of interaction terms would also reduce degrees of freedom, although this is less an issue given the number of observations in this data set.

4. Data

The data set utilised by this paper is the Irish Community Innovation Survey (CIS) 2004-2006. This survey was conducted jointly by Forfás (Ireland's national policy advisory body) and the Central Statistics Office in Ireland. A total of 4,150 surveys were issued with 1,974 responses. This response rate of 48% is high relative to other Irish studies

(Roper 2001; Jordan and O'Leary 2008). The survey is directed to companies employing more than 10 persons engaged in a range of sectors.

The target for the Irish CIS are the complete range of manufacturing sectors with selected service sectors. As this paper focuses on variation in innovation activity across sectors, care must be taken when defining sectoral classifications. When determining these classifications, three factors must be considered. Firstly, it is necessary to ensure that there are substantial differences in the sectoral classifications as, if they are similar, it would be expected that there would be little variation in the innovation activity across these sectors[1]. Secondly, the classifications must reflect a logical, coherent selection of firms which operate in a similar manner. Finally, the sectoral classifications must be broad enough to ensure that a sufficient number of firms fall into each category to provide statistically robust estimations of the models specified in the previous section. Therefore, while it has been standard in some instances to include a vector of NACE2 digit classifications this was not possible for this paper and broad sectoral classifications are generated based on the OECD classification system as detailed below (European Commission 2003).

Four sectoral classifications are chosen which meet the requirements of the three criterion outlined above. These are (i) *High-Tech Manufacturing*, (ii) *All Other Manufacturing*, (iii) *Wholesale, Transport, Storage and Communication* and (iv) *Financial*

[1] As an exaggerated example consider a manufacturing and services firm. These firms are substantially different in the products they offer. Therefore, a broad 'sector' which incorporated both of these firms would not adequately reflect the type of firm within that sector. However, classifying these firms in different sectors would reflect the different characteristics of the firm.

Intermediation. These classifications are made using the NACE Rev 1 codes with the definitions of each sector as *High-Tech Manufacturing* (24, 29, 30 - 35); *All Other Manufacturing* (10-14; 15-37 excluding high-tech, 40-41), *Wholesale, Transport, Storage and Communication* (51, 60-64) and *Financial Intermediation* (65-67). These definitions are in line with those utilised by Doran and O'Leary (2011) and Hall (2009). It can be observed in Table 1 that 15% of firms operate in the high-technology sector, 35% in AOM, 40% in WTS&C and 10% in FI.

[insert Table 1 around here]

The CIS collects information about knowledge sourcing and innovation output in the reference period 2004 to 2006. This paper identifies four forms of innovation output; new to firm (NtF), new to market (NtM), process and organisational innovation. Product innovation is defined as the introduction of a new, or significantly improved, good or service during the three years 2004 to 2006 and can be broken down into NtF and NtM innovation. NtF innovation is defined as the introduction of a new or significantly improved good or service to the firm's market which is already available from competitors. NtM innovation is the introduction of a new good or service to the firm's market, which is not already provided by the firm's competitors.

Process innovation is defined in the CIS as being comprised of three elements; (i) new or significantly improved methods of manufacturing or producing goods or services, (ii) new or significantly improved logistics, delivery or distribution methods for inputs, goods or services or (iii) new or significantly improved supporting activities for processes, such as maintenance systems or operations for purchasing, accounting or computing. Firms which engaged in any of these activities are defined as process innovators. Finally, organisational innovation is defined as (i) new business practices for organising procedures, (ii) new methods of organising work responsibilities and decision-making or (iii) new methods of organising external relations with other firms or public institutions. These definitions of innovation are consistent with the Oslo Manual (2005) and Schumpeter's (1934) definitions of innovation. Table 1 illustrates that 25% of firms introduced NtF innovations, 22% NtM innovations, 31% process innovations and 44% organizational innovators during the reference period.

Key innovation input variables considered in this paper are external knowledge sources and research and development. The Irish CIS defines external interaction as active participation with other enterprises or non-commercial institutions on innovation activities. The CIS identifies seven potential external partners; (i) other group enterprises, (ii) suppliers, (iii) customers, (iv) competitors, (v) consultants, (vi) universities and (vii) public research institutes. Due to the low level of response in the university and public research institute categories the decision was taken to amalgamate these two linkages into one; public interaction. R&D activity is defined as creative work undertaken within an enterprise to increase the stock of knowledge for developing new and improved products and processes. It can be noted from Table 1 that 25% of firms engage in R&D activity while the degree to which firms engage with external knowledge sources varies depending on the agent considered.

Finally this paper also controls for the size of the firms and whether the firm is Irish owned. The average size of firms surveyed in the Irish CIS is 124 with a standard deviation of 525. While 74% of the firms surveyed are Irish owned.

5. Empirical Results

5.1 Results of the Restricted Model

Table 2 displays the probit estimations of equation (1), the restricted model. Included in these estimations are sectoral dummies indicating the sector in which the firm operates, with high-technology manufacturing being the reference category. The results of the likelihood-ratio test for parameter stability across sectors are also presented in Table 2. The null hypothesis is that there is no variation in the parameter estimates of the four distinct sectors.

[insert Table 2 around here]

Initially, it can be observed that the likelihood-ratio statistics, presented at the bottom of Table 2, suggest that it is not possible to reject the null hypothesis for process and organisational innovation. This suggests that the coefficient estimates of equation (1) for process and organisational innovation exhibit stable parameter estimates across sectors and can be confidently interpreted. However, it can be observed that the null hypotheses of parameter stability for NtF and NtM innovation can be rejected. This implies that these parameter values from the estimation of equation (1) are not consistent across sectoral classifications and that the aggregate estimation may provide misleading insights into the innovation activity of firms across these sectors. Therefore, as dictated by the likelihood ratio test, it is not appropriate to discuss the results for NtF or NtM innovation in the aggregate sense. The remainder of this sub-section will focus on the discussion of the aggregate results for process and organisational innovation, while the following section will present the disaggregated results of the estimation of equation (2) for NtF and NtM innovation.

For process innovation, there is no clear evidence of a sectoral difference in the propensity to innovate. Firms in the W,T,S&C sector are less likely to engage in process innovation relative to high-technology firms while firms in the AOM and FI sectors are equally as likely to engage in process innovation as high-technology firms. For organisational innovation, there is no indication that the propensity to innovate varies across sectors. These results, coupled with the results of the likelihood-ratio tests, suggest that regardless of the sector a firm operates in the manner in which the firm generates a process or organisation innovation and its propensity to do so do not vary.

When considering the key drivers of process innovation, it can be noted that external interaction with suppliers and competitors has a significantly positive effect. Similarly, firms which engage in supplier and public research linkages are more likely to engage in organisational innovation. This result is consistent with the international literature; suggesting that external networking is an important source of knowledge for innovation (Freel 2003; Mansury and Love 2008; Roper et al. 2010). However, it also suggests that external linkages are not universally significant, and that only a small number of targeted interaction agents have a positive effect on innovation propensity (Freel 2003; McCann and Simonen 2005).

As is expected, R&D is found to be consistently significant and positive for both process and organisational innovation (Cohen and Klepper 1996). This suggests that firms which engage in internal knowledge generation are more likely to innovate, relative to those firms which do not engage in R&D activities. Interestingly, indigenous firms have a lower likelihood of innovation relative to non-indigenous firms. This may represent the benefits accruing to non-indigenous firms of innovation support or technology transfer from parent or other group companies (Doran and O'Leary 2011). This, essentially economies of scale effect, may not be available to indigenous enterprises who are less likely to be part of a larger industry grouping than non-indigenous enterprises, which are most likely branch plants of multinationals.

5.2 Results of the Unrestricted Model

The likelihood-ratio test results for NtF and NtM innovation suggest that the slope coefficients of the model vary across sectors. Therefore, it is important to provide separate estimates for each sectoral class so as to avoid misinterpreting the results from an incorrectly specified aggregate model. This variation in the drivers of innovation across different sectors is generally consistent with the existing international literature with Pavitt (1984), Oerlemans et al. (1998) and Hall et al. (2009) all indicating that the propensity to innovate varies across sectors. The results of these individual sectoral estimations of equation (2) are presented in Table 3.

[insert Table 3 around here]

It can be observed that there is substantial variation in the drivers of NtF innovation across sectors. Apart from the performance of R&D, no other variable has a consistent effect on the likelihood of NtF innovation. External interaction is only found to be an important driver of NtF innovation in the W,T,S&C sector; in the remainder of the sectors there is no significant external interaction effect. This suggests that for the majority of sectors considered, NtF innovation is primarily driven be internal knowledge generation through R&D. Finally, indigenous firms in the W,T,S&C and FI sectors are less likely to introduce NtF innovations relative to non-indigenous firms.

Turning to NtM innovation, it can be noted that, apart from R&D, the drivers of innovation across sectors vary substantially. Firstly, for firms in the high-technology sector, the key driver of innovation is internal R&D activity. External interaction is found to have no significant effect on the likelihood of innovation. However, for the three remaining sectors, external interaction is found to have a significant effect. Firms in the AOM sector which interact within their group are more likely to introduce NtM innovations; firms in the W,T,S&C sector are more likely to introduce NtM innovations if they interact with their suppliers and customers and firms in the FI sector are more likely to introduct NtM innovations if they interact with competitors and consultants.

Interestingly, a number of negative interaction coefficients are present. Firms in the AOM and W,T,S&C sectors are less likely to innovate if they interact with consultants while firms in the W,T,S&C sector are also less likely to innovate if they interact with competitors. This result suggests the need for targeted interaction by firms (Freel 2003), as oppose to merely open interaction (Laursen and Salter 2006). Finally, indigenous firms in the W,T,S&C sector are less likely to innovate relative to non-indigenous firms.

5.3 Comparing Restricted and Unrestricted Models

The key contribution of this paper is to analyse whether estimations of innovation production functions, in which numerous sectors are included, exhibit parameter stability across sectors. Should parameter stability not be observed, this raises possibilities that results derived from aggregate estimations may be misleading. This section compares the results of the estimations of the restricted model, equation (2), for NtF and NtM innovation against the unrestricted estimation of equation (1). It is noted that the log-likelihood ratio tests indicate the aggregate estimation, of these two forms of innovation, to be unsuitable due to parameter variability across sectors.

Initially, in Table 2, the results indicate that interaction with suppliers and customers have a positive effect on NtF innovation while interaction with consultants has a negative effect on NtF innovation. It is also concluded that indigenous firms are less likely to NtF innovate relative to non-indigenous firms. However, from Table 3, it can be noted that these results are largely driven be the W,T,S&C sector. It is only this sector which exhibits significant interaction coefficients. However, due to the fact that it comprises approximately 40% of the sample, it would appear that this sector drives the significance of these interaction coefficients in the overall model. Therefore, conclusions drawn from Table 2 may suggest that interaction is an important driver of NtF innovation; however, a closer examination suggests that this finding only applies to one sector.

Similar conclusions can be drawn for NtM innovation. Table 2 suggests that interaction with other group agents and suppliers has a positive effect on NtM innovation while interaction with consultants has a negative effect on NtM innovation. However, when analysing Table 3 it can clearly be seen that this does not hold true across all sectors. One important point to note is that while interaction with consultants does indeed have a negative effect on the likelihood of NtM innovation in the AOM and W,T,S&C sectors, it actually has a positive effect on NtM innovation for firms in the FI sector. When combined the AOM and W,T,S&C sectors comprise a total of approximately 75% of the sample, perhaps explaining why a negative coefficient is observed in the aggregate model. This example points to the importance of ensuring that models are specified correctly before deriving innovation policy implications, as a failure to do so may result in the application of an innovation policy which has adverse effects on some sectors.

6. Conclusions and Implications

This paper estimates an innovation production function which analyses the effects of external interaction and internal R&D on firms' innovation performance, using data from the Irish Community Innovation Survey (CIS) 2004-06. While it is common to control for differing propensities to innovate across sectors through the inclusion of sectoral dummy variables in innovation production functions, this implicitly assumes that the importance of innovation inputs do not vary across sectors. In a key contribution, through the estimation of an innovation production function, for four differing types of innovation, and the subsequent testing of these functions for parameter stability across sectors, this paper provides an empirical analysis of whether the importance of innovation inputs vary across sectors.

For new to firm and new to market innovation, the likelihood ratio test indicates that there is parameter instability across sectors. This suggests that there is a strong degree of heterogeneity in the drivers of innovation across sectors. Initially, the results find that for new to firm innovation, business networking is only found to have a significant role in explaining innovation in the wholesale, transportation, storage and communication sector. In the remaining three sectors the main driver of new to firm innovation are internal drivers such as R&D. For new to market innovation it is found that only firms in the high-technology sector do not make use of business networks in their innovation process. However, across the remaining three sectors it is found that networking plays a critically important role in the likelihood of new to market innovation. Interestingly, however, the importance of business networks vary depending on the sector. For example, interaction with other group companies is found to be important for firms in the manufacturing sector while supplier interaction is important for the wholesale, transport, storage and communication sector and consultants are important for the financial intermediaries sector.

The results indicate that the propensity to introduce process or organisational innovations varies slightly depending on the sector in which a firm operates but there is no difference in the mechanisms through which these sectors innovate. This suggests that, regardless of sector, business networking is consistent as is the effectiveness of R&D for these forms of innovation.

These results raise a number of important implications for policy makers. The variability in the driver of innovation across sectors for new to firm and new to market innovation suggests that, by implementing a broad range of innovation support measures or applying a "one size fits all" policy, innovation supports may be less effective than hoped. The results strongly suggest that a nuanced approach, tailored to specific sectors is required. For instance, the results derived in this paper suggest that high-technology firms rely on internal R&D to generate new to firm and new to market innovations while manufacturing firms rely on a mixture of internal R&D and business networking. Therefore, policies aimed at high-technology firms should focus on supporting R&D while policies targeted at manufacturing firms could employ a hybrid strategy of supporting R&D while also aiding the firm in establishing business networks.

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Table 1 – Descriptive Statistics of Key Variables

Variable	Mean	sd
External Interaction		
Group (%)	9	n/a
Supplier (%)	11	n/a
Customer (%)	9	n/a
Competitor (%)	3	n/a
Consultant (%)	6	n/a
Public Interaction (%)	8	
R&D (%)	25	n/a
Control Variables		
Employment	124	525
Irish Owned (%)	74	n/a
Innovation Output		
New to Firm (%)	25	n/a
New to Market	22	n/a
Process (%)	31	n/a
Organisational (%)	44	n/a
Sector		
High-Technology Manufacturing	15	n/a
All Other Manufacturing	35	n/a
Wholesale, Transport, Storage and Communication	40	n/a
Financial Intermediation	10	n/a

Table 2: Probit Estimation of Equation (1) – Unrestricted Model

Variable	**Process Innovator**	**Organizational Innovator**	**New to Firm Innovator**	**New to Market Innovator**
Constant	-0.5528	-0.2929	-0.8262	-0.9492
	(0.1043)	(0.1005)	(0.1050)	(0.1082)
External Interaction				
Group	0.2196	0.1961	-0.0369	0.2717*
	(0.1733)	(0.1729)	(0.1600)	(0.1623)
Supplier	0.6154***	0.6729***	0.4093***	0.4116***
	(0.1545)	(0.1585)	(0.1471)	(0.1494)
Customer	-0.0723	-0.2106	0.4401***	0.2221
	(0.1774)	(0.1776)	(0.1613)	(0.1649)
Competitor	0.6678***	0.0207	0.1934	0.2306
	(0.2451)	(0.2336)	(0.2138)	(0.2188)
Consultant	0.1245	0.2348	-0.4249***	-0.3498*
	(0.1975)	(0.1995)	(0.1801)	(0.1856)
Public Interaction	0.0822	0.3348***	-0.0648	0.0636
	(0.1876)	(0.1889)	(0.1681)	(0.1723)
R&D	1.1032***	0.7989***	1.0975***	1.1993***
	(0.0881)	(0.0866)	(0.0880)	(0.0899)
Control Variables				
Employment	0.0001**	0.0000	0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Irish Owned	-0.2040***	-0.2933***	-0.2625***	-0.2546***
	(0.0825)	(0.0781)	(0.0850)	(0.0899)
Sector[2]				

All Other Manufacturing	-0.0841	-0.0364	-0.1758*	-0.1280
	(0.1064)	(0.1035)	(0.1079)	(0.1110)
Wholesale, Transport, Storage and Communication	-0.1980*	0.0732	-0.1276	-0.2454**
	(0.1100)	(0.1058)	(0.1132)	(0.1189)
Financial Intermediation	-0.2172	0.1971	-0.2537*	-0.5796***
	(0.1433)	(0.1342)	(0.1467)	(0.1625)
No. of obs.	1722	1722	1722	1722
Wald Chi2	447.66	284.18	329.40	423.58
	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.2021	0.1208	0.1760	0.2385
Log-likelihood	-883.65	-1033.87	-771.05	-676.38
LR-Test Restricted versus Unrestricted Model				
LR Chi 2	34.25	28.17	40.86	60.11
Prob > Chi 2	0.1589	0.3502	0.0425	0.0003

Note 1: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level and * indicates significance at the 0.1 level.

2: High-Tech Manufacturing is a reference category

Table 3: Probit Estimation of Equation (2) – Restricted Model

	New to Firm Innovation				New to Market Innovation			
Variable	High-Tech Man.	All Other Man.	W,T,S & C	Financial Inter.	High-Tech Man.	All Other Man.	W,T,S & C	Financial Inter.
Constant	-0.6591	-1.4745	-0.6872	-0.9713	-0.8214	-1.3214	-0.9269	-1.7128
	(0.1569)	(0.1721)	(0.1358)	(0.1854)	(0.1610)	(0.1674)	(0.1474)	(0.2569)
External Interaction								
Group	-0.0819	0.2723	-0.4756	0.5604	-0.0614	0.7933***	0.4773	0.2326
	(0.2922)	(0.2838)	(0.4156)	(0.4730)	(0.2958)	(0.2982)	(0.4272)	(0.5090)
Supplier	0.1152	0.3524	0.6368***	0.0528	0.3204	0.1667	0.9832***	-1.0912
	(0.3123)	(0.2573)	(0.2783)	(0.5141)	(0.3149)	(0.2675)	(0.2791)	(0.7520)
Customer	0.1943	0.2246	1.4240***	-0.3932	-0.1376	0.2109	0.8802***	-0.5886
	(0.2888)	(0.3092)	(0.3868)	(0.6139)	(0.2969)	(0.3194)	(0.3984)	(0.6860)
Competitor	0.0742	0.2390	-0.1321	0.5338	0.3380	0.6842	-1.2215***	1.1333*
	(0.4328)	(0.4229)	(0.4500)	(0.5867)	(0.4462)	(0.4513)	(0.5790)	(0.7149)
Consultant	-0.1358	-0.3250	-0.7812	-0.4508	0.2195	-0.8231***	-1.4495***	2.0648**
	(0.3065)	(0.3066)	(0.5224)	(0.7959)	(0.3159)	(0.3403)	(0.5220)	(1.0846)
Public Interaction	0.2110	0.0508	-0.8523*	-0.5103	0.2138	0.0421	-0.0236	-1.2029
	(0.2716)	(0.2906)	(0.5121)	(0.8646)	(0.2759)	(0.3075)	(0.4869)	(1.1032)
R&D	0.8956***	1.2068***	1.1417***	1.1574***	0.9503***	1.3125***	1.2363***	1.7020***
	(0.1773)	(0.1351)	(0.2080)	(0.2839)	(0.1791)	(0.1381)	(0.2168)	(0.3165)
Control Variables								
Employment	-0.0001	0.0004	0.0000	0.0001	0.0001	0.0007	0.0000	0.0001
	(0.0002)	(0.0004)	(0.0001)	(0.0001)	(0.0002)	(0.0005)	(0.0001)	(0.0001)
Irish Owned	-0.2558	0.2067	-0.6358***	-0.5490**	-0.1297	-0.0684	-0.6673***	-0.1796
	(0.1788)	(0.1693)	(0.1505)	(0.2514)	(0.1820)	(0.1673)	(0.1656)	(0.3079)
No. of obs.	277	591	688	166	277	591	688	166

Wald Chi2	42.78	128.36	101.27	37.26	55.20	158.20	119.39	54.76
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.1142	0.1998	0.1639	0.2115	0.1471	0.2463	0.2303	0.3800
Log-likelihood	-165.89	-257.01	-258.27	-69.44	-160.04	-242.09	-199.52	-44.67

Note 1: *** indicates significance at the 0.01 level, ** indicates significance at the 0.05 level and * indicates significance at the 0.1 level.