# The effectiveness of R&D and external interaction for innovation: Insights from quantile regression

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ABSTRACT

*This paper utilises censored quantile regression techniques to analyse the impact of various forms of innovation inputs on the innovation output of a sample of Irish firms, using data from the Irish Community Innovation Survey 2008-2010. While there is a substantial literature on the drivers of innovation, there is a new and growing research interest in the application of quantile regression in the context of innovation. The advantage of quantile regression is that it moves beyond the typical assumption of variation around a mean, and allows for insights into the changing effectiveness of innovation inputs across the full innovation distribution. However, most papers treat innovation output as a continuous variable, when in fact it is more accurate to treat this variable as censored. Therefore, this paper applies a censored quantile regression estimator to evaluate the impact of innovation inputs on innovation output and to assess whether the effectiveness of these inputs varies, depending on how innovative a firm is. The key results of the paper are that both intramural and extramural R&D decline in effectiveness as firms become more innovative. We also find evidence that external networking is more important for less innovative firms.*

## 1. INTRODUCTION

NOW MORE THAN EVER FIRMS ARE FORCED TO INNOVATE. To survive, to grow, and to secure a competitive advantage they must continuously challenge what they do, challenge themselves to come up with new and different ways of doing things, and constantly improve on the things they already do (Greisendorf 2009). Drucker (1998 p 149) defines innovation as 'the means by which the entrepreneur either creates new wealth-producing resources or endows existing resources with enhanced potential for creating wealth', whilst Edwards and Gordon (1987 p 1) define it as 'a process that begins with an idea, proceeds with the development of an invention, and results in the intro-

duction of a new product, process or service to the marketplace'. Firms engage in various innovative activities which allow them to grow faster, better and smarter than their competitors. But should all firms innovate in the same way? Should the rare innovator, the average innovator, and the star innovator engage in the same type of research and development (R&D) and should they source knowledge from the same place? This paper addresses these issues.

We focus on internal and external drivers of innovation, assessing whether the impact of innovation inputs is consistent for all innovators, or whether the impact varies depending on how innovative a firm is. We use data from the Irish Community Innovation Survey (CIS) 2008-2010 (CSO, 2010) to specify and estimate an innovation production function which relates innovation inputs to innovation outputs (Jaffe 1986; Griliches 1995). However, unlike standard estimations of innovation production functions, which commonly use probit and logit models and, less commonly, ordinary least squares (Roper et al 2008; Hall et al 2009; Doran and O'Leary 2011), we employ censored quantile regression techniques. Very few papers focus on the application of quantile regressions in an innovation context (for exceptions see Coad and Rao 2006, 2008; Ebersberger et al 2010) and these papers typically treat innovation output as a continuous variable.

However, we argue that it is more appropriate to treat innovation output as a censored variable, which is truncated at zero. Therefore, we employ the censored quantile regression method developed by Chernozhukov et al (2015). Through the use of this methodology we can assess whether innovation output is altered in different ways, depending on which part of the innovation distribution we consider, while also controlling for the fact that innovation output is truncated at zero (as firms cannot be negative innovators). It is this new methodological approach which is the main contribution of our paper.

Another relatively novel element of this paper is the focus on innovation turnover, as oppose to binary indicators of innovation output. Specifically, we focus on the natural logarithm of turnover per employee derived from product innovations. The advantage of looking at this form of innovation is that we are not simply looking at the occurrence of innovation, but at the intensity of innovation within the firm (Roper 2001). This alternative measure of innovation output is relatively underutilised in innovation studies, which typically focus on binary indicators of innovation output. However, a problem occurs in utilising innovation turnover, as not all firms are innovators. Therefore, we adopt a two-step methodology in addressing this issue, in line with the work of Crépon *et al* (1998, henceforth CDM), to ensure that our analysis does not suffer from sample selection bias. In the first step, we estimate an innovation decision equation, which controls for firms' decisions to engage in innovation activities. This is accomplished through the use of a standard probit model. We derive an inverse Mill's ratio from this estimation for inclusion in our censored quantile regression analysis, which focuses only on innovative firms, and measures the intensity of innovation using our innovation turnover per

employee measure. This two-step approach is standard in the literature, however to the authors' knowledge no paper has utilised a censored quantile regression model in the second stage.

The remainder of this paper is structured as follows. Section 2 briefly describes the relevant literature for our analysis. Section 3 introduces the data set. Section 4 presents the empirical model to be estimated. Section 5 presents and discusses our empirical results. The final section concludes.

## 2. Literature review

We present a brief review of the literature relevant to our paper in this section. The key literature we discuss focuses on (i) the importance of innovation, (ii) the different innovation inputs likely to impact innovation output and (iii) the value of using quantile regressions to provide insights into the innovation process of firms.

### *2.1 The Importance and Measurement of Innovation*

There is a substantial literature which notes the importance of innovation for the growth and development of firms, regions and countries. Ultimately the goal of innovation is not innovation itself but some form of benefit for business productivity or profitability. Studies by Klomp and Van Leeuwen (2001, 2006), Janz *et al* (2003), Love and Mansury (2007), Roper *et al* (2008) and Hall *et al* (2009) have shown the importance of innovation for firm performance. For example, Klomp and Van Leeuwen (2006) find that innovation success has a positive effect on productivity, and Roper et al (2008) find that innovation output positively affects firms' sales and employment growth.

Given the importance of innovation for productivity, there has been a substantial number of studies conducted on the drivers of innovation. These include papers focusing on what determines the likelihood of innovation output, the proportion of sales derived from innovative goods and services, and the value of innovation turnover. These studies focus on a variety of different drivers such as the geography of innovation (Jaffe 1986; Jaffe *et al* 1993), the importance of external knowledge sources for innovation (Freel 2000b, 2003) and the role of R&D in the innovation process (Crépon *et al* 1998).

In addition to different drivers of innovation, there is also much discussion in the existing literature as to the measurement of innovation. A variety of alternative innovation indicators are used, such as binary indicators of whether a firm innovated, or not, percentage of sales which are derived from new or improved products or services, or the turnover derived from new innovations (Freel 2003; Griffith *et al* 2006; Love and Mansury 2007; Roper *et al* 2008; Doran and O'Leary 2011). Indeed the Oslo Manual (2005) notes that there are many different methods of categorising innovation output, but that studying the turnover from innovative goods and services can provide insights into the innovative performance of firms, which is not possible with simple binary indicators of innovation output. One limitation of this innovation

turnover variable is that it is constrained to certain forms of innovation, and does not consider process or organisational innovation and, therefore, while providing information on innovation success we are confined to studying product innovation. On the other hand, utilising this measure of innovation provides a mechanism to distinguish between the levels of innovativeness of firms. This has been exploited by authors such as Coad and Rao (2006, 2008) and Ebersberger *et al* (2010), who utilise quantile regression to analyse whether the determinants of innovation output vary according to how innovative a firm is.

The current paper seeks to exploit this underutilised innovation measure through the application of a censored quantile regression model, building upon the work of Ebersberger et al (2010) to provide insights into firms' innovation processes which are not observable using standard binary indicators of firms' innovation outputs.

### *2.2 Innovation inputs*

As noted, the literature on innovation suggests that there are a large and diverse number of inputs important for the innovation process. These range from internal inputs to external sources of knowledge. Most studies of innovation highlight the particular importance of R&D for innovation output. Cohen and Levinthal (1989) assert that R&D plays a crucial role in the development of new knowledge and in enhancing firms' absorptive capacity. They note that firms which invest in R&D gain an increased ability to identify, assimilate and exploit knowledge for the generation of new innovations. This hypothesis has been tested empirically by numerous papers, such as Crépon *et al* (1998), Lööf and Heshmati (2002) and Roper *et al* (2008). Cohen and Levinthal (1990) suggest that by undertaking R&D, firms can develop higher levels of absorptive capacity, improving their ability to recognise and assimilate valuable knowledge.

The decision to engage in intramural (internal) R&D rather than extramural (external) R&D has received much attention in the literature (Cohen and Klepper 1996; Love and Roper 2001; Love and Roper 2002; Freel 2003; Cassiman and Veugelers 2006; Love and Mansury 2007; Roper *et al* 2008; Love and Roper 2009; Vega-Jurado *et al* 2009). Geyskens *et al* (2006) argue that the decision is related to transaction cost economics, Stanko and Calantone (2011) argue that it relates to resource based economics, whilst Mudambi and Tallman (2010) argue that a combination of these paradigms is needed to explain the decision. According to transaction cost economics, intramural R&D is preferred when transaction costs are excessive. These relate to adaptation cost (i.e. the costs associated with adjusting contracts with external parties in uncertain environments), safeguarding costs (i.e. the costs of monitoring the external party after a contract is in place) and measurement costs (i.e. the cost of ensuring the contract is fulfilled). Resource based economics, on the other hand, argues that firms will engage in extramural R&D

for activities not central to their resources, while protecting resources critical to their competitive advantage.

Finally, transaction value models integrate transaction costs and resource value and argue that a firm will weigh up both factors when making their decision, and that a firm may be willing to take on higher costs in order to increase the resource value of the company. Thornhill (2006) suggests that the type and size of industry may have a role to play in the firm's decision. For example, in industries where the pace of technical change is high, firms may need fast access to highly skilled workers. One way to access such experts is via extramural R&D (Mudambi and Tallman 2010). In contrast, in more stable industries there may be more time to train and to engage in internal R&D (Thornhill 2006).

A second important input into the innovation process is external interaction (Kline and Rosenberg 1986; Lundvall 1988). Lundvall (1988), Kline and Rosenberg (1986) and Nonaka *et al* (2001), in viewing interactive learning as a positive source of knowledge, suggest that external linkages can be exploited for the advancement of business innovation. When firms innovate they utilise, combine and transform existing knowledge into new products and/or processes. 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. Indeed, in the innovation value chain concept (Hansen and Birkinshaw 2007), external knowledge sources feature prominently. These external sources of knowledge are viewed as being important sources of knowledge and provide insights into the resources available to the firm as well as shifting market dynamics and trends.

As noted in Doran and Jordan (2012) 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).

A substantial literature has also emerged linking sectoral characteristics with innovation performance. For instance 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. With de Jong and Marsili (2006 p 216) noting that these sources and patterns 'shape and differentiate the pattern of innovation of firms across sectors'.

We are particularly interested in this paper in the impact of R&D and external interaction on innovation output, while also controlling for size, ownership and sector. Specifically we ask what is the impact of R&D and external networking on innovation, and does it vary across the distribution of innovation output?

### *2.3 Quantile regression*

The key contribution of this paper is the use of quantile regression to analyse whether the impact of innovation inputs varies across the innovation distribution of the firms in our sample. One could ask why it is important to consider variation across the innovation distribution. Ebersberger et al (2010 p 96), in the context of innovation and R&D, note that '[a]dopting a quantile approach allows researchers to gain a fuller and more complete picture of one of the key relationships that underlies economic growth'. Indeed, Koenker and Hallock (2001 p 151) note that '[t]here is a rapidly expanding empirical quantile regression literature in economics that, taken as a whole, makes a persuasive case for the value of "going beyond models for the conditional mean" in empirical economics'.

In the context of R&D and innovation, Ebersberger *et al* (2010 p 95) estimate a quantile regression for a sample of Finnish firms and note that the relationship between R&D and innovation is 'less straight forward than so far assumed'. They find that the effectiveness of R&D for innovation output varies substantially in different parts of the innovation distribution. In the context of the effect of innovation on turnover, Coad and Rao (2008) note that innovation has the strongest effect on growth for firms in the higher quantiles. Coad and Rao (2006) also analyse the impact of innovation on market value, and find that the impact of innovation varies across the distribution of market value. They find that firms with higher values of Tobin's q are particularly sensitive to innovation, while firms with lower levels of Tobin's q are not sensitive to innovation. Likewise Goedhuys and Sleuwaegen (2010) note that product innovators have a significant positive effect on the growth of firms, especially in the higher quantiles.

This paper adds to the growth literature using quantile regression in an innovation context, by utilising a censored quantile regression model. This builds on previous work by Ebersberger *et al* (2010), by addressing the specific issue of innovation output being truncated at zero. The rationale for implementing a censored model is that our data are truncated at zero, as firms cannot possess negative innovation turnover. Also we contribute to the existing literature by considering not just the impact of internal R&D on the innovation output of firms, but also the impact of extramural R&D and a range of other factors on innovation output. While previous studies have examined these types of factors, typically in a binary innovation outcome system, the use of quantile regression provides additional insights into the varying effectiveness of these innovation inputs across the full distribution of innovators.

## 3 DATA

The data used in this paper are derived from the Irish Community Innovation Survey 2008-2010. This survey was conducted jointly by Forfás (Ireland's national policy advisory body) and the Central Statistics Office in Ireland. The survey is directed to companies employing more than 10 persons engaged in a range of sectors. Consistent with the OECDs Oslo manual, the survey includes a reference period, which in this case is 2008 to 2010, for innovation inputs and outputs (OECD 2005). The target for the Irish CIS is the complete range of manufacturing sectors, along with selected service sectors (CSO 2010). The motivation for the CIS survey is to provide a comprehensive survey of the innovation performance of Irish firms. The survey is conducted as part of the EU-wide Community Innovation Survey project and is completed every two years (CSO 2010).

The key dependent variable in our analysis is the innovation turnover per employee of firms. This is derived from questions relating to the innovation performance of Irish firms captured in the Irish CIS. Firms are required to indicate whether they introduced a product innovation during the reference period 2008 to 2010, where a product innovation is defined as 'the market introduction of a new or significantly improved good or service with respect to its capabilities, user friendliness, components or sub-systems'. The product could be new to the market or new to the firm. 'New to the market' is defined as a new or significantly improved good or service which the firm released onto its market before its competitors, but it may already have been available in other markets. A 'new to the firm' innovation is defined as the introduction by the firm of a new or significantly improved good or service that was already available from competitors in their market.

Having defined these two forms of innovation, firms were then asked to estimate the proportion of their total turnover in 2010 that was due to new to market and new to firm innovations introduced during the 2008 to 2010 period. Using turnover figures obtained from the CSO's central business register for 2010, we use the percentage of turnover derived from innovative goods and services, regardless of whether they were new to the market or new to the firm, to generate a value of turnover from product innovations. The turnover figures are matched to the CIS data by the Irish Central Statistics Office, with the match made at the level of the local business unit. Therefore, the figures reported in the CIS and the Business Register are comparable. As is standard in the literature, we do not consider absolute turnover for innovative goods and services but the natural logarithm of turnover for innovation goods and services per employee. It is worth noting that we are considering only product innovation. We do not consider process, organisational or marketing innovation, as the CIS does not provide information on the amount of turnover derived from these forms of innovations. Therefore, we have two innovation variables. The first, our innovation decision variable, indicates whether a firm is engaged in product innovation or not and takes the form of a binary vari-

able. The second is a censored variable, lying above zero, indicating the quantity of turnover per employee derived from innovative products.

The use of the log of innovation turnover per employee allows us to analyse whether the impact of innovation inputs on innovation outputs varies depending on the innovativeness of the firm. It is impossible to address this with simple binary measures of innovation output, which only indicate whether the firm innovates or not, rather than the intensity with which the firm innovates. Therefore, while our decision to analyse innovation turnover per employee limits the scope of our analysis to just product innovation, it allows us to analyse this type of innovation in more depth. The use of alternative measures of innovation output are not possible, given the methods employed by this paper (i.e. ordinal indicators cannot be used when estimating tobit style models).

Regarding inputs into the innovation process, we consider various measures of R&D, external interaction and firm specific factors. Starting with R&D, we employ two measures; intramural and extramural R&D. Intramural R&D is defined as creative work undertaken within the firm to increase the stock of knowledge for developing new and improved products and processes, whilst extramural R&D is defined as the same activities as intramural R&D, but performed by other firms or by public or private research organisations and purchased by the firm. The use of these two forms of R&D allow us not only to assess the importance of R&D for innovation, but also whether the effectiveness of R&D conducted in-house or sourced from external sources varies.

When we consider external interaction agents, the CIS provides information on six different possible sources of external knowledge. As per Love *et al* (2014), we categorise a firm as being open to external networks if they engage in any form of external interaction. Therefore, if a firm engages in networks with their customers, suppliers, competitors, consultants, universities or public research institutes, we classify that firm as sourcing knowledge from external agencies and being open to networks.

The final variables considered are included to control for potential firm heterogeneity. We include a measure of firm size as the log of the number of employees in the firm. We also control for whether the firm is Irish owned or not, as a number of studies using the Irish CIS have indicated that Irish firms are less innovative than foreign owned firms (Doran and O'Leary 2011; Doran *et al* 2012). Finally we control for the sector in which the firm operates, as there can be considerable variation in the propensity of firms to innovate across sectors (Pavitt 1984). Unfortunately, while age has also been found to have an important impact on firms' innovation output, the Irish CIS does not include this variable and therefore we cannot include it on our model. However, we would anticipate that age and size would be highly collinear, with younger firms being smaller and older firms being larger. Therefore, while not ideal, out of necessity we assume that size may also capture age effects.

Table 1 presents the descriptive statistics of all of the variables of interest used in this study. We can see that the average innovation output per employee of firms is €113,959, with a high standard deviation of €653,979. We can also note that firms spend more on extramural R&D per employee than intramural R&D per employee, with firms' expenditure on intramural and extramural R&D being €6,157 and €1,442 respectively. The average size of the firms in our sample is 153, while 66 per cent of the firms are Irish owned.

Table 1: Summary Statistics of Data

| *Variables* | *Mean* | *Standard Deviation* | *Min* | *Max* |
|---|---|---|---|---|
| *Innovation Turnover* | €113,959 | €653,979 | €0 | €10,300,000 |
| *R&D* | | | | |
| Intramural R&D | €6,157 | €18,621 | €0 | €365,727 |
| Extramural R&D | €1,442 | €9,118 | €0 | €223,596 |
| *Networking* | | | | |
| Backwards | 29.6% | Na | 0 | 1 |
| Forwards | 22.8% | Na | 0 | 1 |
| Horizontal | 7.3% | Na | 0 | 1 |
| Public | 19.8% | Na | 0 | 1 |
| *Control Variables* | | | | |
| Size | 153 | 461 | 10 | 10,234 |
| Irish Owned | 66% | Na | 0 | 1 |

Source: Irish Community Innovation Survey

## 4. Empirical method

The central question of this paper is the measurement of the differentiated impact of innovation inputs on innovation output, dependent upon how innovative a firm is. Therefore, we construct an innovation production function which relates innovation inputs to innovation outputs. However, as we are considering only innovative firms, we must first model innovative behaviour, as is standard with the CDM literature (Crépon *et al* 1998; Griffith *et al* 2006; Klomp and Van Leeuwen 2006). This is applied to correct for sample selection bias, as we are moving from a random sample which is representative of the population under consideration (i.e. the Irish CIS), to a non-random selection of innovative firms (i.e. only the innovative firms in the CIS). Therefore, following Doran and O'Leary (2011), we initially estimate a binary innovation decision equation. This is displayed as equation (1):

$$ID_i = \alpha_0 + \alpha_1 X_i + \mu_i \quad (1)$$

Where $ID_i$ is a binary variable which indicates whether firm $i$ engaged in product innovation activity or not, $X_i$ is a matrix of control variables which may determine a firm's innovation decision,[3] $\alpha_1$ are the corresponding coefficients and $\mu_i$ is the error term. As is standard in the CDM methodology, equation (1) is estimated using a probit model, and the inverse Mill's ratio (IMR) is derived from the equation for inclusion in subsequent analysis. The use of the IMR in subsequent equations mitigates for sample selection bias, as the remainder of the analysis no longer deals with a random sample of firms, but only the innovators from the original random sample (Doran and O'Leary 2011).

Following from our first stage estimation, we start the main element of our analysis by specifying an innovation production function with the log of innovation turnover per employee as our dependent variable; and we run our analysis only for innovative firms. This function relates innovation inputs to innovation outputs and is standard in the innovation literature (Griliches 1995; Crépon *et al* 1998; Griffith *et al* 2006).

$$IO_i = \beta_0 + \beta_1 R\&D_i + \beta_2 EI_i + \beta_3 Z_i + \beta_4 IMR_i + \varepsilon_i \quad (2)$$

where $ID_i = 1$. In equation (2) $IO_i$ is the log of the turnover per employee derived from innovative products or services for firm $i$ (where $i=1,\ldots,N$). $R\&D_i$ is a N by 2 matrix containing information on the log of intramural and extramural R&D expenditure per employee. $\beta_1$ is the 2 by 1 vector of coefficients. $EI_i$ is a binary indicator of whether firm $i$ engaged in any form of networking activity. $\beta_2$ is the associated coefficient. $Z_i$ is a matrix containing a series of control variables which may impact on the likelihood of a firm innovating. These are the size of the firm, whether the firm is Irish owned or foreign owned and the sector the firm operates in. $\beta_3$ is the associated vector of coefficients. $IMR_i$ is the inverse Mill's ratio derived from equation (1). $\varepsilon_i$ is the error term.

When it comes to estimating the innovation production function, the standard approach is to use logit or probit models when the innovation indicator is binary (Griffith *et al* 2006; Hall *et al* 2009), some variation of OLS if the variable is continuous (Crépon *et al* 1998) or a censored regression, such as a tobit model, if the innovation indicator is the proportion of sales from innovative good or services (Roper 2001). We build upon the approach used by Ebersberger *et al* (2010), which is one of the few papers to use quantile regression. However, rather than utilising a standard quantile regression, we note that our data are essentially censored at zero, as the dependent variable is innovation turnover per employee. Therefore, we employ a censored quantile regression model to take account of the censored nature of the data. The advantage of quantile regression is that it allows the coefficients to vary over

the distribution of the dependent variable. It can explain the determinants of the dependent variable at any point of the distribution of the dependent variable (unlike OLS which is limited to explaining the mean of the dependent variable). Therefore, we can assess whether the contribution of R&D and knowledge sourcing inputs to innovation output are the same for average, rare and star innovators.

The estimator employed is that developed by Chernozhukov *et al* (2015), which is a censored quantile regression estimator based on the censored quantile regression model developed by Powell (1986). The advantages of utilising this estimator in the innovation production function context is that it enables an analysis of the effect of innovation inputs on innovation output, allowing for the importance of innovation inputs to vary across quantiles while also controlling for the censored nature of the data, whereby firms cannot possess an innovation output of less than zero. For a detailed discussion of the estimator we refer the interested reader to Chernozhukov *et al* (2015) and for an example of this estimator in practice, see Kowalski (2015).

## 5. Results

Regarding the estimations of our empirical model, we present graphs of the coefficients and their confidence intervals from the censored quantile regression estimation of equation (2) in Figure 1; and a table of coefficients in Table 2. Specifically we focus our discussion on the role on intramural and extramural R&D (as well as their interaction), engaging in networks, and size, on the innovation output of firms.

Regarding Figure 1, we present a separate graph for each of our independent variables (with the corresponding coefficients presented in Table 2). The Y-axis shows the magnitude of the coefficient estimates, while the X-axis shows the quantile used in the estimation. The quantiles range from 10 to 90, with 50 being the median. A horizontal line would indicate that the coefficients do not vary across quantile, implying that regardless of the portion of the distribution we analyse, the impacts of the independent variables are constant. However, we can see clearly that all of the graphs appear to exhibit non-horizontal trends, implying that the impact of the coefficients varies over the distribution. The dark shaded area of the graphs corresponds to the confidence intervals of the coefficients.

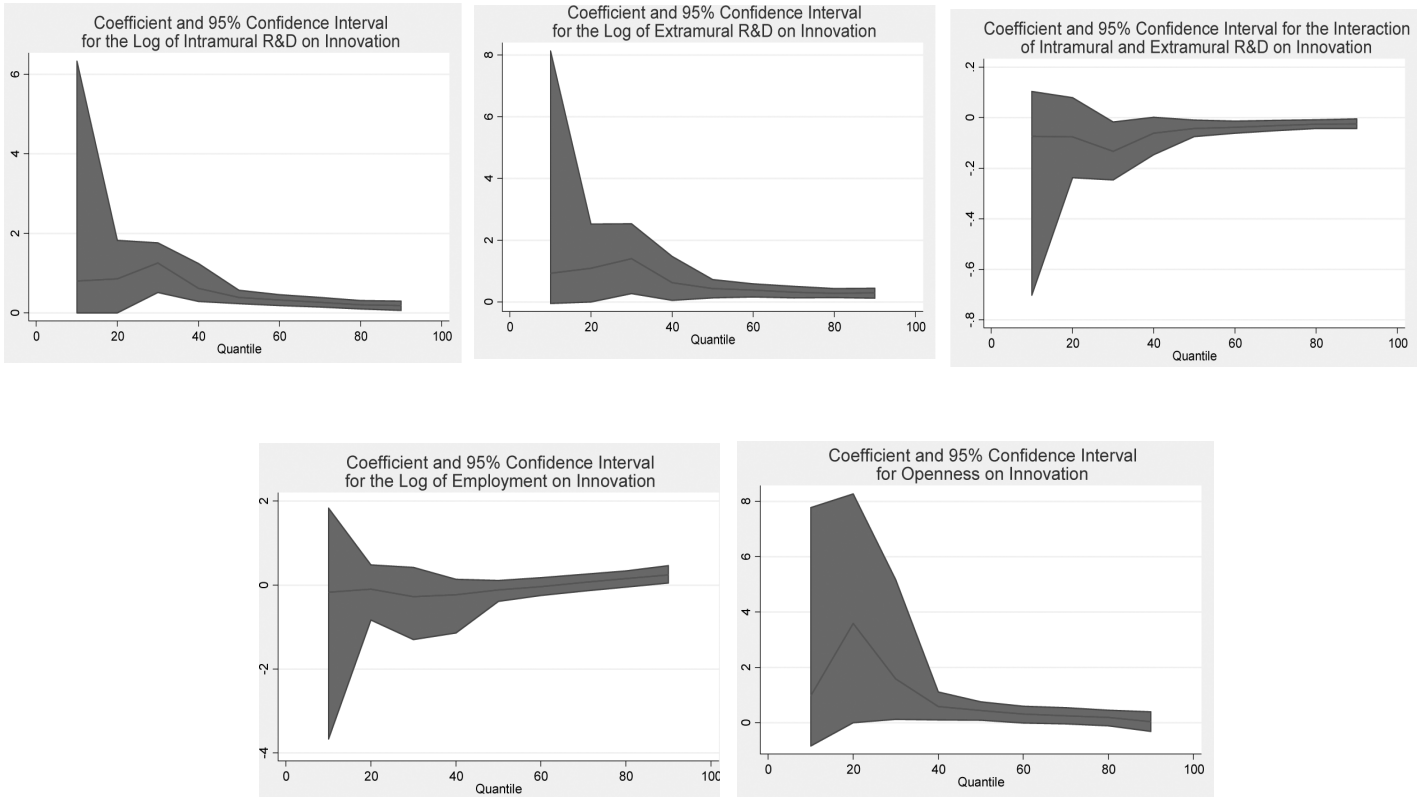
Beginning with intramural R&D, we note that this has a consistent positive effect on innovation output. However, there is a pronounced downward trend in the magnitude of the coefficient after the 30th percentile. This suggests that as we approach higher levels of innovation output, the return to each additional unit of intramural R&D per worker diminishes. It would appear that less innovative firms gain more of a benefit from each additional euro of R&D than more innovative firms. This may be due to diminishing returns to R&D as firms become more innovative. Firms which have little inno-

Table 2: Estimates of Censored Quantile Regression Estimation of Equation (2)

| *Quantile* | *10* | *20* | *30* | *40* | *50* | *60* | *70* | *80* | *90* |
|---|---|---|---|---|---|---|---|---|---|
| *Intramural R&D* | | | | | | | | | |
| Lower 95% CI | 0.0000 | 0.0000 | 0.5162 | 0.2916 | 0.2319 | 0.1846 | 0.1497 | 0.0987 | 0.0608 |
| Coefficient | 0.8007 | 0.8572 | 1.2592 | 0.6143 | 0.3872 | 0.3259 | 0.2641 | 0.2015 | 0.1853 |
| Upper 95% CI | 6.3251 | 1.8249 | 1.7594 | 1.2395 | 0.5715 | 0.4597 | 0.3913 | 0.3088 | 0.2940 |
| *Extramural R&D* | | | | | | | | | |
| Lower 95% CI | -0.0548 | 0.0000 | 0.2665 | 0.0404 | 0.1276 | 0.1607 | 0.1284 | 0.1325 | 0.1167 |
| Coefficient | 0.9251 | 1.0815 | 1.3973 | 0.6176 | 0.4264 | 0.3752 | 0.3124 | 0.2735 | 0.2849 |
| Upper 95% CI | 8.1328 | 2.5185 | 2.5319 | 1.4685 | 0.7189 | 0.5828 | 0.4955 | 0.4267 | 0.4360 |
| *Interaction term R&D* | | | | | | | | | |
| Lower 95% CI | -0.7026 | -0.2379 | -0.2463 | -0.1459 | -0.0748 | -0.0616 | -0.0513 | -0.0429 | -0.0427 |
| Coefficient | -0.0731 | -0.0761 | -0.1329 | -0.0610 | -0.0423 | -0.0381 | -0.0310 | -0.0256 | -0.0247 |
| Upper 95% CI | 0.1047 | 0.0789 | -0.0167 | 0.0020 | -0.0090 | -0.0126 | -0.0106 | -0.0085 | -0.0039 |
| *Log of Employment* | | | | | | | | | |
| Lower 95% CI | -3.6681 | -0.8289 | -1.2966 | -1.1406 | -0.3868 | -0.2514 | -0.1412 | -0.0490 | 0.0505 |
| Coefficient | -0.1737 | -0.1018 | -0.2750 | -0.2362 | -0.1162 | -0.0393 | 0.0649 | 0.1525 | 0.2441 |
| Upper 95% CI | 1.8311 | 0.4748 | 0.4201 | 0.1405 | 0.1040 | 0.1705 | 0.2584 | 0.3375 | 0.4591 |
| *Open to Networking* | | | | | | | | | |
| Lower 95% CI | -0.8376 | 0.0000 | 0.1212 | 0.1022 | 0.0975 | -0.0127 | -0.0424 | -0.1127 | -0.3116 |
| Coefficient | 0.9793 | 3.5837 | 1.5904 | 0.5930 | 0.4365 | 0.3193 | 0.2523 | 0.1915 | 0.0352 |
| Upper 95% CI | 7.7697 | 8.2610 | 5.1700 | 1.1183 | 0.7587 | 0.5949 | 0.5423 | 0.4512 | 0.3953 |
| *Irish Owned* | | | | | | | | | |
| Lower 95% CI | -0.5394 | -0.4263 | -0.1015 | -0.2325 | -0.4007 | -0.5195 | -0.6178 | -0.8147 | -1.3840 |
| Coefficient | 1.5738 | 2.4646 | 1.3480 | 0.4389 | 0.0560 | -0.1411 | -0.2653 | -0.3738 | -0.7617 |
| Upper 95% CI | 11.0386 | 9.5760 | 2.9389 | 1.3784 | 0.5819 | 0.2523 | 0.1596 | 0.0683 | -0.2436 |

Notes 1: Controls for sector are also included but not presented here due to space constraints. 2: The estimation method used is the censored quantile regression developed by Chernozhukov et al (2015).

Figure 1: Selected Coefficients and Confidence Intervals from Estimation of Equation (2)



vation output may gain more of a benefit from R&D, as the additional technological steps to acquire new knowledge may be lower than firms with higher levels of innovation output, if we assume that more innovative firms are operating at the technological frontier. This corresponds with Thornhill (2006), who suggests that in industries where the pace and magnitude of change is fast, firms need quick access to highly skilled workers, whereas in slower industries there is time to train employees and to conduct in-house R&D.

Regarding extramural R&D we observe a very similar pattern occurring. While the effects seem to be slightly larger than intramural R&D, the largest positive effect again occurs around the 30th percentile. Again, it would thus appear that less innovative firms gain more of a benefit from each additional euro of R&D than more innovative firms, suggesting diminishing returns to R&D as firms become more innovative.

We also consider the interaction of intramural and extramural R&D. We note that in this case there appears to be some degree of substitutability between these two forms of R&D. The coefficient term is consistently negative, implying that firms substitute intramural and extramural R&D. However, the confidence intervals suggest that this result is not significant for the bottom 50 per cent of firms, only becoming significant from the 50th percentile and above. This implies that at the lower end of the innovation distribution, there is no relationship between intramural and extramural R&D, but as firms become more innovative they substitute one for the other.

Considering the engagement of a firm in networks, we note a positive relationship between innovation output and networking. While the largest effect again occurs around the 30th percentile, we note that the confidence bands are very wide for this particular variable and often take in zero. Therefore, we are reluctant to draw any strong implications from our analysis regarding networking. While the effects appear positive, these are not statistically relevant to innovative performance.

Regarding our firm specific factors we find that size has no significant effect on innovation output. There is substantial debate in the literature as to the impact of size on innovation and its connection with R&D, with alternative studies producing conflicting results (Cohen and Klepper 1996; Freel 2000a; Hall *et al* 2009; Murro 2012). In our case we observe no scale effects.

## 6. Conclusions and implications

This paper analyses the determinants of the innovation output of Irish firms. The novel element of the paper is to employ censored quantile regression techniques to assess whether the return to various innovation inputs varies across the distribution of innovation output. The data used are from the Irish Community Innovation Survey 2008-2010, which surveys the innovation performance of over 2,000 Irish firms. Of necessity our analysis is confined to the analysis of product innovators, so our sample reduces to just over 900 firms.

However, in order to avoid any bias arising from sample selection issues, we estimate a two-step model, following Doran and O'Leary (2011) in the CDM literature tradition. While a number of authors analyse the drivers of innovation performance in Irish firms, none use censored quantile techniques and only a few use measures of innovation output which are non-binary.[4]

We expand upon previous studies which have used quantile regression in two ways. Firstly by utilising a recently developed censored quantile regression technique; and secondly by focusing not solely on intramural R&D, but expanding our analysis to consider other important drivers of innovation output such as extramural R&D (OECD 2005) and external interaction agents (Freel 2003; Hansen and Birkinshaw 2007). In doing so we contribute to the literature on the drivers of innovation and the extent to which the returns to innovation inputs vary across the spectrum of innovation outputs of firms.

The key results of the paper are that the returns to innovation inputs vary substantially, depending upon the portion of the innovation distribution considered. Also there is substantial variation in the types of returns observed, with no clear pattern, such as higher returns for all variables for highly-innovative firms, observed. A key finding is that the returns to intramural and extramural R&D vary significantly across the distribution of innovation output. The greatest return to intramural and extramural R&D is for less innovative firms. This suggests that firms gain more from their R&D activity at earlier levels of innovativeness; and that as they become more innovative, the effectiveness of each euro spent on R&D diminishes.

This paper opens avenues for future research into the innovation processes of firms. It notes that the returns to innovation inputs vary dramatically in the Irish case. However, there is little research which employs quantile regression in other countries and thus little opportunity for comparison across countries. Analysis of other countries' CIS data, using quantile regression, would provide scope for comparison across countries, which may show further heterogeneity in the effectiveness of innovation inputs. The procedures used here could also be employed to assess the impact of innovation on the productivity performance of firms. It may be that more or less productive firms gain more or less of a benefit from the introduction of innovations.

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3. Where the matrix of variables includes the sector a firm operates in, the size of the firm controls for intramural and extramural R&D and whether the firm is Irish owned or not.

4. Examples of studies which use a continuous or censored measure of innovation output, but not quantile regression, are Roper *et al* (2008) and Doran and O'Leary (2011).

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