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REVIEW ARTICLE

INFORMATION AND COMMUNICATION TECHNOLOGY (ICT) AND R&D FOR INNOVATION AND PRODUCTIVITY

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ABSTRACT

Business innovation is regarded as an important driver of productivity growth. In this paper, it is investigated that R&D and ICT investment at the firm level in an effort to assess their relative importance for innovation. Explicitly, it is used a refined version of the CDM model that includes ICT and R&D investment as the two main inputs into innovation and productivity, and test it on a firm-level panel data set based on the recent four waves of the innovation survey for India. Two measures of innovative output are tested, i.e., four types of innovation (product, process, organizational and marketing innovation) and number of patent applications. It is found that R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation, and ICT being more important for productivity. These results suggest that ICT is an important driver of productivity growth that could explain the "Indian productivity puzzle", i.e., the feature that India having a relative low level of R&D intensity. The results also indicate considerable differences between firms in Manufacturing and Services with respect to innovation and productivity effects of ICT, R&D and human capital.

KEYWORDS

Innovation, ICT, R&D, Productivity, CDM model, Manufacturing and Services.

1. INTRODUCTION

Business innovation is regarded as a potentially important driver of productivity growth both at the firm and at the national level. At the micro level, business innovation has the potential to increase consumer demand through improved product or service quality and simultaneously decrease production costs [1-3]. More importantly, strong business innovation at the macro level increases multifactor productivity thus lifting international competitiveness, economic growth and real per capital incomes [4]. Therefore, it is of great interest to businesses and policy makers alike, to identify those factors which stimulate innovation and to understand how these factors interact. One obviously important factor behind innovations is R&D, but it is not the only one. The availability of high skilled workers is mentioned as another important factor and recently more and more attention is drawn to the role of Information and Communication Technology (ICT) as an enabler of innovation [5].

ICT is one of the most dynamic areas of investment as well as a very pervasive technology. ICT is often referred to as a modern general purpose technology, GPT [6, 7]. The possible benefits of ICT use for a firm include among others savings of inputs, general cost reductions and greater flexibility of the production process. This technology may also stimulate the innovation activity in the firm leading to higher product quality and creation of new products or services. Its use has the potential to increase innovation by improving communication possibilities and speeding up the diffusion of information through networks. For example, technologies that allow staff to effectively communicate and collaborate across wider geographic areas will encourage strategies for less centralized management leading to organisational innovation. Previous analysis confirms that ICT play an important role for firm performance, *e.g*. Brynjolfsson and Hitt [8, 9], and Gago and Rubalcaba [10]. These studies evaluate effects of ICT use and innovation on productivity. A few recent studies, i.e., Hall et al. [11] and Vincenzo [5], focus on the direct link between ICT and innovation. One aim of the current study is to assess the effects of ICT as an enabler of innovation in Indian firms and assess its relative importance for innovation compared to R&D. Are they complements or substitutes? Do effects differ for different types of innovations? Four types of innovations are under investigation: a new (or improved) product, a new (or improved) production process, an organisational innovation and a new marketing method.

Another aim of the study is to investigate whether a broad ICT-use in India could explain the so-called "Indian puzzle", i.e., while R&D spending in the Indian business sector as a share of GDP is below the The Organisation for Economic Co-operation and Development (*OECD*) average, the productivity performance of Indian firms are among the strongest in OECD. Several studies try to give some explanation to the "Indian puzzle" (also referred to as the Indian productivity paradox). OECD points to the skill level of the adult population and financial support from the public sector as positive factors behind the strong productivity performance in India, while finding the weakness in innovation activity in India to be in the manufacturing sector. Castellacci [12] claims that the source of Indian productivity paradox is in the sectoral composition of the economy. Recently, Asheim [13] discusses the lack of registration of all inputs and outputs in innovation activities and points to underreporting of R&D investments and innovation activities in the national R&D statistics. Giving several possible explanations for the "Indian puzzle", none of these studies, however, mention the high level of diffusion of ICT in India. For example, 60.3% of Indian firms had access to broadband already in 2017 while the average for at this time was 46.5% (see Figure 1). Also in 2015, when most of Indian firms had access to broadband (average for became 89.2%), India was one of the leaders among Asian countries in e-commerce (see Figure 2). This fact

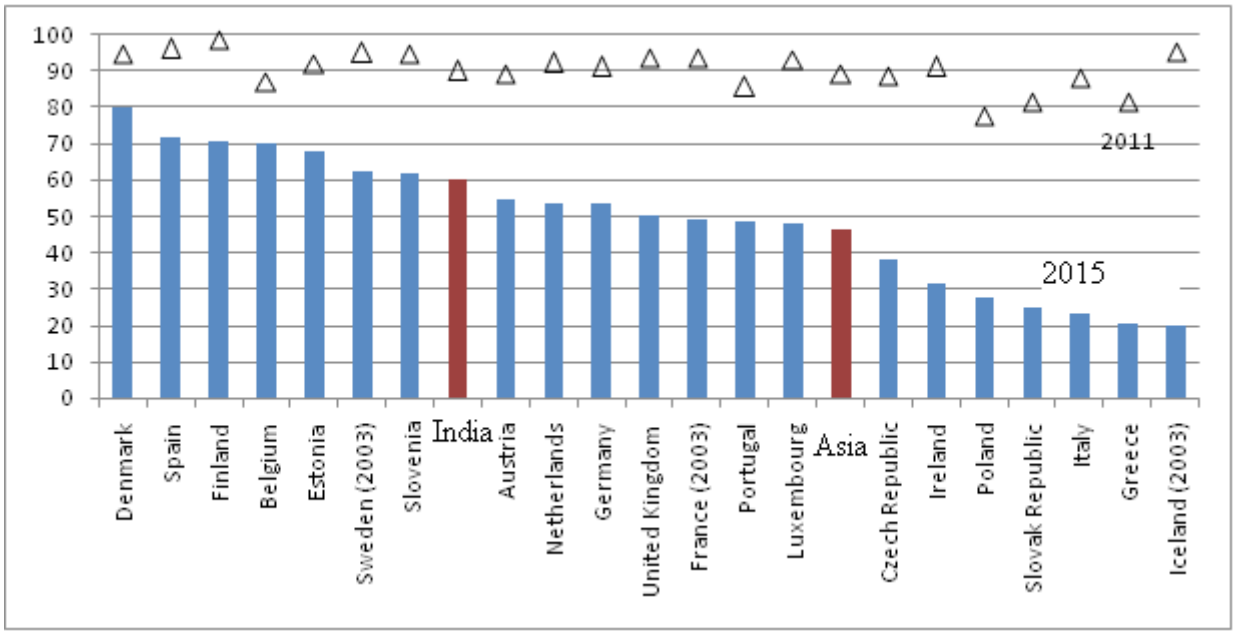

Figure 1: Business Use of Broadband in 2015 and 2011 (Δ): Entreprises with 10 or More Employees. Source: OECD, Key ICT Indicators.

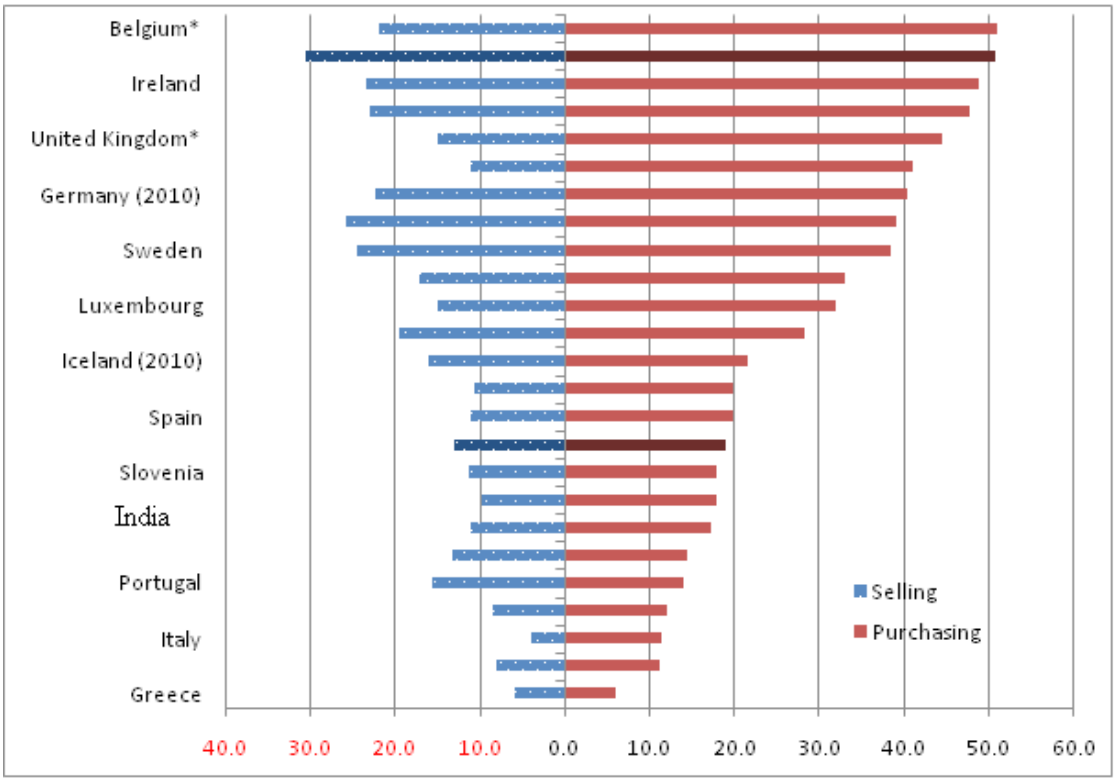

Figure 2: Internet Selling and Purchasing, all Industries in 2017.

is one of the reasons why the current paper directs its attention to data on Indian firms. What is the relative importance of ICT for productivity compared to other key inputs such as R&D and human capital?

To investigate these research questions it is applied the most currently used model for analysing the innovation input-innovation output-productivity link, i.e., the so-called CDM model [1]. The standard version of CDM model is a structural model that studies the following interrelated stages of the innovation chain: the choice of a firm whether or not to engage in R&D; the amount of resources it decides to invest in R&D; the effects of these R&D investments on innovation output; and the impacts of innovation output on the productivity of the enterprise. In the spirit of Hall et al. [11], it is relied in this paper on a refined version of the CDM model, which treats ICT investment together with R&D as two main inputs into innovation and productivity. While Hall et al. [11] base their study just on the manufacturing firms, Rogers [14] compare manufacturing firms with firms in services and such comparison seems to have substantial importance. If one checks the development of total factor productivity (TFP) in different industries in India compared to their U.S. industry equivalents in the three last decades, one can see that most changes have happened in the Wholesale and retail trade sector (see Figure 3). While the productivity level in the Manufacturing industry remained between 60 and 70 per cent below the productivity level in the U.S. during 1978-2015, the Wholesale and retail trade sector showed a great increase in relative TFP and by 2007 had almost reached the U.S. level. At the same time the Wholesale and Retail trade sectors are among the three most ICT capital intensive sectors in India [12], i.e., the average share of ICT capital services in total capital services in 2002-2006 is 26.8 per cent for the Wholesale and 17.4 per cent for the Retail trade industries (the corresponding share for the Manufacturing sector

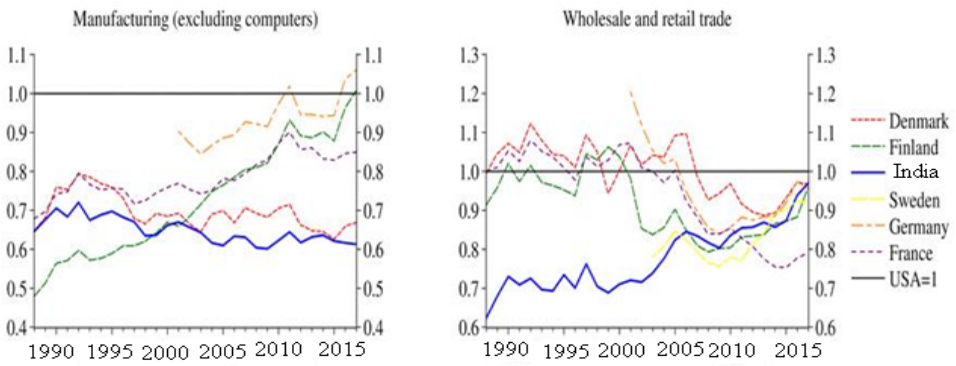

Figure 3: TFP Levels in Manufacturing and Wholesale and Retail Trade in 1990-2017.

is just 5.7 per cent). Hence, it is very important to account for industry heterogeneity when studying the effects of ICT. In order to account for such heterogeneity it provides results for manufacturing firms and firms in services separately (in addition to the analysis of the whole economy). Keeping in mind the explanations of the "Indian puzzle" in the previous studies it also take into account the skill level of employees in Indian firms when analysing effects of ICT on innovation and productivity.

For the analysis, it uses a rich firm-level panel data set based on the four recent waves of the Community Innovation Survey for India: CIS2009 (period: 2008–2011; N = 4655), CIS2011 (period: 2011–2013; N = 6443), CIS2013 (period: 2013–2015; N = 6012) and CIS2015 (period: 2015–2017; N = 6595). Innovation survey data contain information on the inputs and outputs of firms' innovative activities, i.e., how much firms spend on R&D in the year of the survey and whether firms have introduced different types of innovation (product, process, organisational and marketing innovation) over the three-year period before each survey. While four types of innovation reflect the variation in the innovative process, they say nothing about the scope of innovation. Thus, it also uses a count of patent applications from a patent database as a measure of innovative activity in the firm. By supplementing these data with information on ICT investment and information from different registers, it obtains an unbalanced panel of 14533 observations on 8554 firms, which it treats, however, as a cross-section data. The estimation results confirm that R&D and ICT are both strongly associated with innovation and productivity, with R&D investment being more important for innovation, and ICT investment being more important for productivity. These results suggest that ICT is an important driver of productivity growth that should be taken into account when trying to explain the "Indian productivity puzzle". The results also indicate considerable differences between firms in Manufacturing and Services with respect to productivity effects of ICT, non–ICT and human capital.

The paper is organized as follows. Section 2 summarizes the main findings by previous studies and explains the refined version of the CDM model. Section 3 presents the data set, main variables and some descriptive evidence. Section 4 discusses estimation of the empirical model and provides the results and Section 5 draws the main conclusions.

2. THEORETICAL FRAMEWORK

2.1 ICT and firm performance

Several previous analyses confirm that ICT plays an important role in business success. One of the first attempts to estimate the role of IT assets on the firm performance in the form of productivity was made by Brynjolfsson and Hitt [13]. Since then a broad variety of empirical studies has emerged exploring the impacts of ICT on firm performance. Most of these studies employ a production function framework to estimate the elasticity of output with respect to ICT capital, controlling for the amount of other inputs among them innovations. However, very few of them focus on the direct link between ICT use and innovation. As Castiglione [7] puts it "ICT makes it possible to reduce transaction costs, improve business processes, facilitate coordination with suppliers, fragment processes along the value chain (both horizontally and vertically) and across different geographical locations, and increase diversification". Each of these efficiency gains provides an opportunity for innovation. For example, technologies that allow staff to effectively communicate and collaborate across wider geographic areas will encourage strategies for less centralized management leading to organisational innovation.

ICT also enables closer links between businesses, their suppliers, customers, competitors and collaborative partners, which are all potential creators of ideas for innovation (see Rogers [14]). By enabling closer communication and collaboration, ICT assists businesses to be more responsive to innovation. For example, having broadband Internet, web presence and automated system linkages, assists businesses to keep up with customer trends, monitor competitors' actions and to get rapid user feedback, thereby assisting them to exploit opportunities for all types of innovations.

Gretton et al. [15] suggest the following two reasons why business use of ICT encourages innovative activity. Firstly, ICT is a "general purpose technology" which provides an "indispensable platform" upon which further productivity-enhancing changes, such as product and process innovations, can be based. For example, a business which establishes a web presence sets the groundwork from which process innovations, such as electronic ordering and delivery, can be easily developed. In this way, adopting general purpose ICT makes it relatively easier and cheaper for businesses to develop innovations. Secondly, the spill over effects from ICT usage, such as network economies, can be sources of productivity gains. For example, staffs in businesses which have adopted broadband Internet are able to collaborate with wider networks of academics and international researchers more closely on the development of innovations. A lack of proper control for intangible assets and the differences in industrial structure, specifically the smaller ICT producing sector, are seen as main candidates for explaining the differences in productivity growth that are observed between Europe and the U.S. (for comparative analysis of productivity growth in Europe and U.S. see, e.g., Van Ark et al. [4]. It is also true that the R&D investment and ICT investment shares in GDP by firms in all sectors are lower in Europe than in the United States and the ICT gap is somewhat larger than that for R&D. Hall et al. [11] report so high rates of return to both ICT and R&D investments for Italian firms that they suspect considerably underinvestment in both these activities. Another line of literature motivates the importance of ICT for firm organisation [8]. Case studies reveal that the introduction of information technology is combined with a transformation of the firm, investment in intangible assets, and changes in the relation with suppliers and customers. Electronic procurement, for instance, increases the control of inventories and decreases the costs of coordinating with suppliers, and ICT offers the possibility for flexible production: just-in-time inventory management, integration of sales with production planning, et cetera. The available econometric evidence at the firm level shows that a combination of investment in ICT and changes in organisations and work practices facilitated by these technologies contributes to firms' productivity growth. For instance, Castiglione [7] use Innovation surveys data for the UK and find a positive effect on firm performance of the interaction between IT and organizational innovation. Gago and Rubalcaba [10] find that businesses which invest in ICT, particularly those which regard their investment as very important, or strategically important, are significantly more likely to engage in services innovation. Van Ark et al. [4] shows that e-sales and broadband use affect productivity significantly through their effect on innovation output. Broadband use, however, only has a direct effect on productivity if R&D is not considered as an input to innovation. This approach is further developed by Hall et al. [11]. Their study finds that

ICT investment is important for all types of innovation in services, while it plays a limited role in manufacturing, being only marginally significant for organisational innovation. Crepon et al. [1] find, in contrast, that a more intense use of ICT brings about a reduction in R&D effort in German firms. The results for 9 OECD countries in Vincenzo [5] are consistent with ICT having a positive impact on firm innovation activity, in particular on marketing innovation and on innovations in services. However, there is not any evidence that ICT intensive firms have higher capacity to introduce "more innovative" (new-to-the-market) products suggesting that ICT enables rather adoption of innovation than developing of truly new products. Hall et al. [11] find for Italian manufacturing firms that ICT investment intensity is associated with product and organizational innovation, but not with process innovation, although not having any ICT investment is strongly negative for process innovation.

These few recent papers, which investigate R&D and ICT investment jointly, have produced conflicting results on the impact of ICT on innovation. In addition, the observed industry differences suggest that new ICT applications, such as broadband connectivity and e-commerce, are more important in services than in manufacturing. In this paper, it explores the effects of ICT on two different measures of innovation, i.e., four types of innovation that reflect the variation of innovative processes in the firm; and count of patent applications that reflect the scope of innovation, i.e., the firm's capacity to develop truly new products rather than adoption of innovation. It carries out analysis for the whole sample of Norwegian firms and also compares results for manufacturing firms versus firms in services.

2.2 Modeling framework

The currently most used model for analysing the innovation input-innovation output-productivity link is the so-called CDM model [1]. It was applied, for instance, in Lööf and Heshmati [16] and Parisi et al. [3]. The standard version of the model contains three different stages: (1) First, the firm decides whether to start to invest in R&D; if so, then the firm sets the amount of resources it wants to invest in R&D activities; (2) subsequently, the innovative input leads to an innovative output (e.g. product or process innovation, patents, organisational change); (3) finally, the innovative output leads to an improvement of the labour productivity of the firm. Several recent studies have modified the standard CDM model in order to include other factors than R&D in the knowledge production function, e.g., Castellacci [17] investigates the effects of industry-level competition on Norwegian data by use of the CDM model, while ICT is implemented in the CDM model by Lehr and Lichenberg [18] for Netherland and by Hall et al. [11] for Italy.

In this paper, it follows Rogers [14] and Hall et al. [11] and uses a refinement of the standard CDM model that analyses the effects of ICT on different stages of the innovative process. The extension of the CDM model is presented in the diagram in Figure 4. While Rogers [14] use ICT just as an additional input in the knowledge production function and not in the production function; it follows the strategy of Hall et al. [11]. In their version of the refined CDM model ICT is an input both in the production function and in the knowledge production function. While the former inclusion reconciles with a more traditional view that ICT leads to productivity gains (e.g., through implementing of new work practices and, hence, cost reduction and improved output); the latter inclusion introduces a less traditional view, i.e., that ICT may also stimulate the innovation activity in the firm by speeding up the diffusion of information, favouring networking among firms, enabling closer links between businesses and customers, and leading to creation of new goods and services. Consequently, this modelling framework treats ICT as a pervasive input rather than as an input in the production function only.

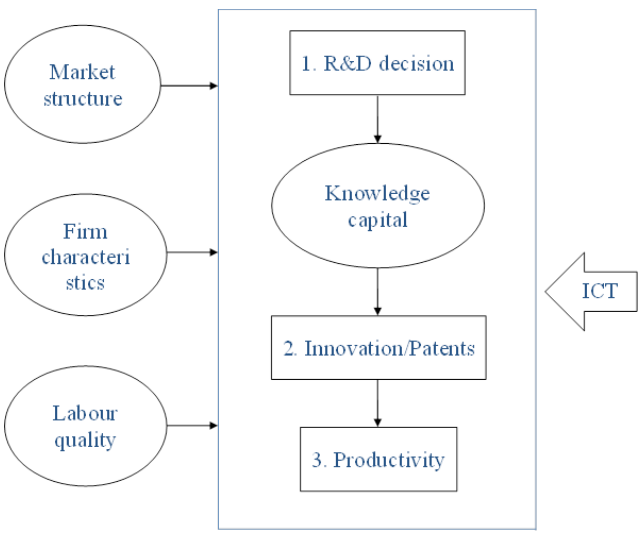

Figure 4: Refined CDM Model with Augmented ICT.

The element of novelty compared to Rogers [14] and Hall et al. [11] is the inclusion of marketing innovation in the analysis in addition to product, process and organizational innovation. All four types of innovation are broadly represented in the data, and, hence, providing analysis for the whole set of innovation types is important for better understanding of the innovation process in the firm. Another element of novelty is the usage of the number of patent applications as an alternative proxy for innovation output. While the combination of different innovation types shows the variety of innovative process in the firm, number of patent applications reflects the scope of the innovation process, i.e., only the best innovative products are expected to be protected by patent. As it mentioned earlier, it is very important to account for industry heterogeneity when studying the effects of ICT. While Hall et al. [11] provide results just for manufacturing firms, following Rogers [14] also provided separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). The more detailed description of different model stages is as follows:

(1) Stage 1: R&D input decision

This stage does not differ from the standard CDM model. It models the firm decision to involve in R&D activities, i.e., first, the firm decides whether to start to invest in R&D; if so, and then the firm sets the amount of resources it wants to devote R&D investments. This statement of the problem can be modelled with a standard sample selection model [18]:

$$I^*(R) = FSR^1\alpha^1 + \varepsilon^1 \tag{1}$$

where FSR^1 is a set of firm-specific characteristics (e.g. size, age, international orientation, etc.), α^1 is the associated coefficient vector and $I^*(R)$ is a latent indicator variable that expresses some decision criterion such that a firm decides to invests in R&D if $I^*(R)$ is larger than some constant threshold $\bar{c}$ (for simplicity, I omit time and firm indexation here).

Once an enterprise has decided to engage in R&D activities, it must set the amount of resources devoted to R&D investments:

$$R\&D^* = FSR^2\alpha^2 + \varepsilon^2 \cdot \tag{2}$$

Analogous to the previous equation and in line with the standard formulation of the CDM model, the latent R&D intensity of a firm in the given period ($R\&D^*$) is represented as a function of another set of firm-specific characteristics FSR^2. The observed R&D intensity is then equal to the latent R&D intensity $R\&D^*$ if $I_R^* \geq \bar{c}$ and zero otherwise. The pair of random disturbances ε_{it}^1 and ε_{it}^2 is assumed to be jointly i.i.d. normally distributed. This model can be further estimated by a maximum likelihood procedure.

(2) Stage 2: Innovation output

Let us now consider a model of how innovation occurs. R&D efforts lead to innovation output. Let $U^* = U(R\&D)$ be a latent variable that measures the extent of creativity/research activity within the firm. The higher the value of U^* is the higher is the likelihood that an innovation will occur. With no loss of generality, one may assume that an innovation takes place when U^* is positive, otherwise no innovation will occur (for simplicity, I again omit time and firm indexation here):

$$INNO = \begin{cases} 1 & \text{if } U^* > 0 \\ 0 & \text{else} \end{cases} \quad (3)$$

This modelling framework is influenced by Griliches [19], Crepon et al. [1] and Parisi et al. [3]. The main idea in this literature is that by investing in R&D, the firm accumulates a knowledge capital stock, which plays an important role in its innovation activities. A refined version of the CDM model also includes ICT investment together with R&D investment into the knowledge production function:

$$U^* = FSI\beta + \delta_1 \cdot R\&D + \delta_2 \cdot ICT + \eta \quad (4)$$

where FSI is a vector of different firm characteristics important for innovation output (e.g., firm size, industry, cooperation in R&D projects, etc.) and η is a normally distributed error term. Then using binary regression models (applied, e.g., in Griffith et al. [2], for product and process innovation; in Rogers [14], for product, process and organizational innovation; and in Hall et al. [11], for product, process and organizational innovation), one can estimate the probability of innovation output (*INNO*) as function of the firm's R&D efforts, ICT investment and relevant firm characteristics:

$$\Pr(INNO = 1 | FSI, R\&D, ICT) = \frac{1}{1 + \exp\{-(FSI\beta + \delta_1 \cdot R\&D + \delta_2 \cdot ICT\}} \quad (5)$$

It used two proxies for innovation output in the empirical estimation at stage 2 of the model, i.e., (i) the probability of four different types of innovation (product, process, organisational and marketing innovation) and (ii) the number of patent applications. In the former case a system of four equations for binary indicators of corresponding types of innovation can be estimated as a quadrivariate probit model. In the latter case, since numbers of patent applications are observed as integer numbers with many zero observations, one can model them as zero inflated count data and use pseudo maximum likelihood for the estimation (see Greene, [20], for description of the model and Crepon et al. [1], and Aghion et al. [21], for application of count data models for the patent data). Note that the variables *R&D* and *ICT* are endogenous here because these investments are simultaneously determined with innovation activities (It is discussed this issue in more detail under empirical model estimation in Section 4).

(3) Stage 3: Production function

The final stage of the CDM model focuses on the effects of innovation output on labour productivity. In order to incorporate firm's ICTs in the standard CDM model it follows the ICT and productivity literature [22] and use the traditional Cobb-Douglas production function with labour and two types of capital as inputs:

$$Y_{it} = F(A_{it}, K_{it}, ICTK_{it}, L_{it}) = A_{it} K_{it}^{\gamma_1} ICTK_{it}^{\gamma_2} L_{it}^{\gamma_3} \quad (6)$$

Here Y_{it} is output of firm *i* in period *t*, measured as value added in constant prices, K_{it} and $ICTK_{it}$ are the corresponding amounts of conventional (non–ICT) and ICT capital inputs in constant prices, L_{it} is the labour input measured as number of employees, and A_{it} is the technical level term. The parameters γ_1, γ_2 and γ_3 correspond, respectively, to output elasticities of two types of capital and labour. Dividing with L_{it} and taking logarithms on both sides of yields:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \gamma_3^* l_{it} + \pi_1 INNO_{it} + FSP_{it}\pi_2 + \zeta_{it} \quad (7)$$

where the small letters *lp*, *l*, *k* and *ictk* denote the logarithm of the labour productivity *Y/L*, labour input *L* and capital intensities, *K/L* and *ICTK/L* correspondingly, $\gamma_3^* = (\gamma_1 + \gamma_2 + \gamma_3 - 1)$ and the technical level term A_{it} is expressed as:

$$\ln(A_{it}) = \pi_0 + \pi_1 INNO_{it} + FSP_{it}\pi_2 + \zeta_{it} \quad (8)$$

Here $INNO_{it}$ is a vector of innovation output variables and FSP_{it} is a vector of different firm specific characteristics that are important for productivity (for instance, firm size, age and location); π_1 and π_2 are vectors with the corresponding coefficients; and the error term ζ_{it}, which comprises measurement errors and firm–specific productivity shocks, is assumed to be white noise. It also allowed for heterogeneous labour input. Both economic theory and empirical evidence suggest that there is a key link between the skill level of the workforce and economic performance. Hence, omitting heterogeneity in the quality of labour may lead to overstating the productivity of ICT capital and innovation output. To account for this bias, it decomposed a firm's workforce into employees who are high-skilled (with at least 13 years of education) and low-skilled (with less than 13 years of education). Letting N_h and N_l denote the corresponding amounts of man-hours (with total amount of man-hours $N = N_h + N_l$) and θ denote the productivity differential of high-skilled workers compared to low skilled workers, effective labour input L_{it} is specified as:

$$L_{it} = N_{l,it} + (1+\theta)N_{h,it} = N_{it}(1 + \theta h_{it}) \quad (9)$$

Here $h_{it} = N_{h,it} / N_{it}$ denotes the share of hours worked by high-skilled workers in the firm. Taking logarithm of and inserting the expression for l_{it} it into yields:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \gamma_3^* n_{it} + \gamma_4 h_{it} + \pi_1 INNO_{it} + \pi_2 FSP_{it} + \zeta_{it} \quad (10)$$

where the approximation follows from $\ln(1 + \theta h_{it}) \approx \theta h_{it}$ and $\gamma_4 = \gamma_3^* \theta$. The inclusion of skill–shares in the production function specification as in in order to control for heterogeneity of labour quality is a very common approach in the literature [22-24]. At this stage I use OLS for estimation.

3. VARIABLES CONSTRUCTION AND DESCRIPTIVE STATISTICS

3.1 Data sources and variables

For the analysis, it uses a rich firm-level panel data set based on the four recent waves of the Community Innovation Survey for India: CIS2006 (period: 2009–2011; *N* = 4655), CIS2011 (period: 2011–2013; *N* = 6443), CIS2013 (period: 2013–2015; *N* = 6012) and CIS2015 (period: 2015–2017; *N* = 6595). These data are collected by Statistics India as a part of the annual R&D survey (it refers to them as *R&D* statistics). They contain information on the inputs and outputs of firms' R&D and innovative activities, e.g., how much firms spent on R&D in the year of survey and whether firms have introduced different types of innovation over the three-year period before each survey. The firms included in the surveys represent a large and representative sample of the Indian private sector. The sectoral coverage is broad, and it comprises around 40 two-digit level industries. These data then are supplemented by information on the number of patent applications from the Patent database and ICT investments from Structural statistics for the years 2011–2017. Finally, by supplementing these data with information on firms and employees from different registers and excluding firms with incomplete information or with extreme observations for the key variables, it obtains an unbalanced panel of 14533 observations on 8554 firms. Table 1 presents an overview of the main variables and the data sources applied in the study. The data sources are described in more detail in Appendix A.

Four types of innovations are under investigation: a new (or improved) product for the firm, *pdt*, a new (or improved) production process, *pcs*, an organisational innovation, *org*, and a new marketing method, *mkt*. The definitions of these types of innovation comply with the recommendations of the Delhi manual. For definitions and examples of different types of innovations see Appendix B. Firms are asked in the Innovation survey to answer whether the firm has introduced a given type of innovation during the last three years. The variable *inno* indicates whether the firm has introduced any type of innovation during the last three years. The corresponding dummy variables are measures of how innovative the firm is and are considered as dependent variables in the analysis of innovation output.

Very few studies use patent applications as a proxy for innovation output (see the original version of the CDM model in Crepon et al. [1], where

Table 1: Overview over Key Variables and Data Sources.

Variable	Definition	Data source (s)
pdt	Introduction of a new product (dummy)[a]	R&D statistics
pcs	Introduction of a new production process (dummy)[a]	R&D statistics
org	Introduction of an organisational innovation (dummy)[a]	R&D statistics
mkt	Introduction of a new marketing method (dummy)[a]	R&D statistics
inno	Introduction of any innovation (dummy)[a]	
sumpat	number of patent applications[a]	Patent database
L	number of employees	R&D statistics
R	R&D investment[b]	R&D statistics
ICT	ICT investment[b]	Structural statistics
ICTK	ICT capital services[b,c]	Structural statistics
K	non-ICT capital services[b,c]	Accounts statistics
Y	value added[b]	Accounts statistics
h	share of man-hours worked by high-skilled employees[d]	REE/NED
Derived variables:		
r	R&D intensity: *R/L* (log)	
ict	ICT intensity: *ICT/L* (log)	
ictk	ICT capital intensity: *ICTK/L* (log)	
k	capital intensity: *K/L* (log)	
l	number of employees (log)	
lp	labour productivity: *Y/L* (log)	

[a] Measured over the three years period preceding the year of the survey.
[b] The units of measurement are thousands of NOK in real terms(base year = 2009).
[c] The variable is measured at the beginning of the year.
[d] Man-hours according to labour contracts.
The number of employees, *L*, is a standard measure of firm size.

they include such a variable). This is, probably, due to the lack of that information at the firm level. In this paper it takes advantage of having access to such data and use the number of applications for a patent, *sumpat*, as another measure of how innovative the firm is. This is a stock variable, which is simply the total number of the Indian patents applied for by the firm through the Indian Patent Office over the three years in the given subperiod. While the introduced innovation types show the *variety* of innovative process in the firm, the number of patents reflects the *scope* of the innovation process, i.e., only best innovative products are expected to be protected by patents.

R&D investment, *R*, is annual R&D investment as it is reported in the questionnaire, deflated by the R&D deflator used in the national accounts (here and later all monetary measures are recalculated in the 2009 prices). Then R&D intensity, *r*, is simply calculated as the R&D investment per employee. Since 2010, Statistics India has collected micro level information on investment expenditures on ICT, i.e., on purchased hardware and purchased and own account software. Then ICT investment, *ICT*, is the total annual ICT expenditures. As deflators for obtaining real expenditures it uses the National Account price indices of corresponding investments. Then by analogy to R&D intensity, ICT intensity, *ict*, is calculated as the ICT investment per employee. These two variables are used as the main input variables into the innovation output equation. The ideal measure capturing the economic contribution of capital inputs in a production theory context is flow of capital services [25]. In very few studies the authors construct a measure of ICT capital based on information about investments in hard- and software [22]. Following PIM Perpetual Inventory Method (PIM procedure) applied in these studies and using information on ICT flows over consecutive time periods it constructs a measure of ICT capital services, *ICTK*. Further, the variable *K* is a measure for non-ICT capital services, which are calculated based on the book values of a firm's tangible assets (see, Rogers [14], for details of construction procedure for both capital measures). Then ICT and non-ICT capital intensities, *ictk* and *k*, that are used in the production function analysis, are calculated as the correspondent capital stock per employee. Firm final output, *Y*, is measured as value added in constant prices and defined as operating revenues minus operating expenses plus wage bills. This variable and *K* were deflated by CPI.

Finally, for each firm, it distinguishes between two types of employees: those with high education (corresponding to completed high school or vocational training) and those without. The variable *h* is defined as the number of man-hours worked by employees with high education divided by the total number of man-hours in the firm. It assumes that labour heterogeneity can also influence the innovation activity in the firm and control for it not only in the production function but also in the innovation output equation. In addition to the main variables described above it uses following firm-specific characteristics in the analysis:

- *Market location*: a set of dummy variables indicating whether a firm sells its *main* products and services in local/regional, national, or other international markets. This variable indicates the location of firm's main competitors. The former category (local/regional market location) is the reference category.

- *Part of a group*: a dummy variable indicating whether a firm belongs to a group.

- *Received subsidy*: a dummy variable indicating whether a firm has received a subsidy for carrying out R&D during the three years of the survey.

- *Hampering factors* (*H*): a set of categorical variables indicating whether a firm considers the following factors as important obstacles to its innovative activities: 'high costs', 'lack of qualified personnel', and 'lack of information'. These variables take values from 0 ("no importance") to 3 ("highly important").

- *Positive R&D history*: a dummy variable indicating whether a firm has carried out any R&D during the three years before the observation year.

- *Cooperation in innovation*: a set of dummy variables indicating whether

the firm cooperated with others (another firm or with a university/ research institute) in India, Delhi, or the rest of the world, when carrying out R&D during the three years of the survey.

- *Purchased R&D*: a dummy variable indicating whether a firm has purchased R&D from external providers.

- *Firm age*: a set of dummy variables indicating the firm age, i.e., 0-2, 3-5, 6-9, 10-15 or 16 years old and older. The latter category (mature firms) is the reference category.

- *Firm industry*: a set of dummy variables indicating the firm industry at two-digit level (see Appendix A for the description of the included industries). Wholesale industry (NACE 51) is the reference industry.

- *Firm location*: a set of dummy variables indicating the region where the firm is located, i.e., North, South, West, East, mid-India, and capital region (Delhi). The latter category is the reference category.

- *Year*: a set of time dummy variables indicating the year of the Innovation survey. 2015 is the reference year.

4. EMPIRICAL MODEL ESTIMATION

4.1. Econometric model specification and estimation issues

The econometric model specification for the refined version of CDM model presented in Section 2 is the following:

(1) Estimation stage 1: R&D input decision

This stage is the same for all model specifications. It models firm's R&D input decision and contains two R&D equations

$$I^*(R_{it}) = FSR_{it}^1\alpha^1 + \varepsilon_{it}^1 \tag{11}$$

$$r_{it}^* = FSR_{it}^2\alpha^2 + \varepsilon_{it}^2 \tag{12}$$

(2) Estimation stage 2: Innovation output

It uses two proxies for innovation output when estimating the model, i.e., the probability of innovating and the number of patent applications. The probability of innovating on its turn can be estimated for four different types of innovation (product, process, organisational and marketing innovation) and in general for any innovation. The innovation equation for the probability of different types of innovation is:

$$\begin{cases} pdt_{it}^* = FSI_{it}\beta^1 + \delta_1^1 \cdot r_{it}^* + \delta_2^1 \cdot ict_{it} + \delta_3^1 \cdot h_{it} + \eta_{it}^1 \\ pcs_{it}^* = FSI_{it}\beta^2 + \delta_1^2 \cdot r_{it}^* + \delta_2^2 \cdot ict_{it} + \delta_3^2 \cdot h_{it} + \eta_{it}^2 \\ org_{it}^* = FSI_{it}\beta^3 + \delta_1^3 \cdot r_{it}^* + \delta_2^3 \cdot ict_{it} + \delta_3^3 \cdot h_{it} + \eta_{it}^3 \\ mkt_{it}^* = FSI_{it}\beta^4 + \delta_1^4 \cdot r_{it}^* + \delta_2^4 \cdot ict_{it} + \delta_3^4 \cdot h_{it} + \eta_{it}^4 \end{cases} \tag{13}$$

the innovation equation for the probability of any type of innovation is:

$$inno_{it}^* = FSI_{it}\beta^5 + \delta_1^5 \cdot r_{it}^* + \delta_2^5 \cdot ict_{it} + \delta_3^5 \cdot h_{it} + \eta_{it}^5 \tag{14}$$

and the patent equation is specified as a heterogeneous count data process with an expectation $sumpat_{it}^*$ conditional on R&D, ICT and other variables:

$$\begin{aligned} &E(sumpat_{it} \mid r_{it}^*, ict_{it}, h_{it}, FSI_{it}, \eta_{it}^6) = \\ &\exp(FSI_{it}\beta^6 + \delta_1^6 \cdot r_{it}^* + \delta_2^6 \cdot ict_{it} + \delta_3^6 \cdot h_{it} + \eta_{it}^6) \end{aligned} \tag{15}$$

(3) Estimation stage 3: Productivity

The productivity equation is:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \gamma_3^* L_{it} + \gamma_4 h_{it} + INNO_{it}^*\pi_1 + FSP_{it}\pi_2 + \zeta_{it}, \tag{16}$$

where $INNO^*$ is either the set of dummies for the different combinations of innovation types: (0,0,0,1), (0,0,1,0), (0,1,0,0), ..., and (1,1,1,1) with combination (0,0,0,0) as the reference category; or the predicted probability of any innovation; or the expected number of patent applications per employee.

This empirical model is a nonlinear system of four recursive equations, each of which focuses on one of the steps of the innovation process. The first equation estimates the probability that an enterprise with firm-specific characteristics FSR_{it}^1 engages in R&D activities. It is estimated for the whole sample of firms. The second equation focuses instead only on firms doing R&D and studies how the R&D intensity of the firm (r_{it}^*) is affected by a set of firm-specific characteristics (FSR_{it}^2). The third equation analyses the link between two main innovation inputs (R&D and ICT) and innovation output (four different types of innovation, or any innovation, or the number of patent applications). Finally, the fourth equation estimates the effects of innovation output together with ICT capital on the labour productivity of the firm (*lpit*). At the second and third stages I also explore the influence of skill composition in the firm (h_{it}) together with firm-specific characteristics FSI_{it} and FSP_{it}, correspondingly. Different firm-specific characteristics and other explanatory variables used in the equations (11)-(14) are described in Table 2.

The choice of explanatory variables such as Market location, Part of a group, Received subsidy and Cooperation in innovation is inspired by both Hall et al. [11] and Rogers [14]. However, it includes the Cooperation in innovation (at the national, Delhi, Indian or world level) and Purchased R&D variables also in the Innovation output equation. The results in Cappelen et al. [26] show that firms collaborating with others in their R&D are more likely to be successful in their innovation activities and patenting, supporting my choice. Following Castellacci [17] who estimates the CDM model on Indian data, it also includes Hampering factors (high costs, lack of qualified personal and lack of information) in the estimation of the R&D choice model (11). As Castellacci [17] demonstrates, these factors are highly relevant for shaping the innovative process and are also valid instruments for the handling the endogeneity problem of the R&D intensity variable when using it in the innovation output equation. While Hall et al. [11] control for the skill composition in the firm in the innovation output equation only; it follows the standard CDM model in Crepon et al. [1] and control for the skill composition of the workforce (share of high-skilled man-hours) also in the productivity equation, with providing of robustness checks for inclusion of that variable both for innovation output and productivity equations.

Several important econometric issues arise in the estimation of this type of CDM model. The first is the possible sample selection bias due to the fact that only a fraction of the firm population innovates; whereas a large number of enterprises in the sample are not engaged in R&D activities at all (only 30 per cent of the observations in the final sample have positive R&D values). In addition, the firms may have some kind of innovative effort but it is not always reported [2] and some firms, while reporting, may underestimate their R&D (e.g. when it is performed by workers in an informal way). In line with the previous CDM empirical studies, it corrects for the selection bias by estimating of (11) and (12) as a system of equations by maximum likelihood assuming that the error terms in (11) and (12) are bivariate normal with zero mean and covariance matrix given by:

$$\begin{pmatrix} 1 & \\ \rho\sigma_\varepsilon & \sigma_\varepsilon^2 \end{pmatrix} \tag{17}$$

In the literature this model is often referred to as a Heckman selection model [27] or type II Tobit model [28]. For identification of such a model vector FSR^1 in the selection equation (11) should contain at least one variable that is not in the vector FSR^2 in the outcome equation (12). All previous works in the CDM literature use, however, the same explanatory variables in both equations (few of them use a non-linear functional form for identification, e.g., Hall et al. [11]. The main reason for this practice is that it is difficult to find the factors explaining a

Table 2: Variables, Instruments and Estimation Methods at Different Model Stages.

	(11) R&D choice	(12) R&D intensity	(13) Innovation output	(14) Productivity
Dependent variable:	Dummy for R&D>0	Log (R&D spending per employee)	Probability to innovate (pdt, pcs, org, mkt) / number of patent appl.	Log (VA per employee)
Log employment	*FSR*[1]	*FSR*[2]	*FSI*	*FSP*
Log employment squared	*FSR*[1]	*FSR*[2]	*FSI*	*FSP*
Positive R&D history	*(FSR*[1]*)*			
Market location	*FSR*[1]	*FSR*[2]	-	-
Part of a group	*FSR*[1]	*FSR*[2]	-	-
Hampering factors	*FSR*[1]	*FSR*[2]	-	-
Received subsidy	-	*FSR*[2]	-	-
Cooperation in innovation	-	*FSR*[2]	*FSI*	-
Purchased R&D	-	-	*FSI*	-
Log(R&D intensity)	-	-	r^*	-
Log(ICT intensity)^	-	-	*ict*	*ictk*
Share of high skilled	-	-	*h*	*h*
Log(non-ICT intensity)^	-	-	-	*k*
Innovation output	-	-	-	*INNO***
Age dummies	*FSR*[1]	*FSR*[2]	*FSI*	*FSP*
Industry dummies	*FSR*[1]	*FSR*[2]	*FSI*	*FSP*
Regional dummies	*FSR*[1]	*FSR*[2]	*FSI*	*FSP*
Time dummies	yes	yes	yes	yes
Estimation method:	Maximum likelihood (ML) by Heckman procedure		Qudrivariate probit by GKH simulation / pseudo ML for zero inflated negative binomial count data	OLS

Notes: * Predicted from step (12); ** predicted from step (13).
Instruments: (.) for estimation of step (12), for estimation of step (13), for estimation of step (14).
^ Set to zero when corresponding investment is zero and dummies for such observations are included.

firm's likelihood to engage in R&D that are not related to the amount of resources the enterprise decides to invest in R&D. In addition to the non-linear functional form (i.e., a quadratic in the log of firm size) it uses historical observations on firm's R&D investments (i.e., whether a firm had any R&D activity in the previous 3 years) as an "exclusion restriction" at this step of the model. On the one hand, it believes that those firms that have earlier R&D experience have higher probability to engage in R&D activities in the given period; on the other hand, it is not obvious that having R&D experience imply higher R&D intensity in the given period (it can happen that "new" R&D investors or those firms that had a break in investing in R&D invest more intensively in R&D in the given period than those firms that invest continuously). It elaborates more on the selectivity issues when estimating the model and check for the appropriate choice of explanatory variables and of an "exclusion restriction" as well as the sensitivity of the results to that choice in Appendix C.

The second econometric issue refers to the endogeneity of some of the main explanatory variables. Since (11)-(14) is a system of recursive equations, it is natural to assume that the main explanatory variable in Equation (14) (innovation output) is endogenously determined in the previous innovation stage, i.e., in innovation equation (13); in turn, the main explanatory variable in Equation (13) (innovation input) is determined in the previous innovation stage, i.e. the R&D intensity equation (12). The standard CDM model handles this problem of the R&D intensity endogeneity by predicting R&D intensity r_{it}^* from the first stage of the model and using it as an input variable in the innovation equation (13). If all explanatory variables in the R&D equation (12) are exogenous, endogeneity of R&D variable in (13) is then controlled for. Correspondingly, to handle the endogeneity of innovation output variable in (14), CDM model uses predicted values of innovation output variable $INNO_{it}^*$ from the second stage in the model as input variable in the productivity equation (14). For that purpose it generates the predicted probabilities of the $2^4 = 16$ possible combinations of four types of innovation (all of which exist in my data) and use them as input variables in (14). Again, one need to have instruments that allow identification of such a model, i.e., vector FSR^2 in the R&D intensity equation (12) should contain at least one variable that is not in the vector FSI in the innovation equation (13), which in its turn should contain at least one variable that is not in the vector FSP in the productivity equation (14). Table 2 provides information about the instruments used at different stages of model estimation and Appendix C provides an assessment of choice of different explanatory variables and instruments.

One should also keep in mind the possible endogeneity of other input variables, i.e., the *ict* variable in Equations (13) and the *ictk* and *k* variables in (14). As to possible endogeneity of the ICT intensity variable, *ict*, in (13), following Hall et al. [11] I first use the reported values of ICT investments in year *t* and treat them as exogenous to innovation output, and then it checks the robustness of the results by including the lagged ICT capital as an input in Equations (13), $ictk_{t-2}$, i.e., an ICT capital in the start of the corresponding survey period; or by instrumenting and including the predicted values of the ICT intensity variable, as Rogers [14] do. As to the capital variables *ictk* and *k* in (14), they are by construction calculated at the beginning of the year *t* and, hence, can be treated as exogenous inputs relative to productivity in the year *t*.

Next, since it has a panel data set (pooled data from the four waves of the innovation survey: CIS2011, CIS2013, CIS2015 and CIS2017), it is important to think on the appropriate panel estimation strategy. However, there are few observational units with more than one year per firm (about 60 percent of firms are represented only once in the sample with average number of observations per firm being 1.6). At this stage of the analysis it prefers keeping all available observations and, for each of the four equations, use pooled data estimation adjusting standard errors for the clustering at the firm level.

Finally, the timing of the questions of the survey is such that one

cannot really claim a direct causal relationship between R&D and ICT investment and innovation, since the latter is measured over the preceding three years in the questionnaire, while R&D and ICT investment are measured in the year of the questionnaire. Therefore the reported results should be viewed as representing associations rather than causal relationships.

4.2 Empirical results

In this sub-section, the estimation results of the augmented CDM model are presented. The first stage (R&D input decision) is estimated using the whole sample. Since one may expect that the importance of innovation modes can differ between industries, the second (Innovation output) and third (Productivity) stages are also estimated separately for manufacturing and services.

(1) Estimation stage 1: R&D input decision

It first tests for selection in R&D reporting and provide the same test as in Hall et al. [11], where one first estimate a probit model where the presence of positive R&D expenditures depends on a set of defined firm characteristics. After having estimated this model, one can for each firm recover the predicted probability of having R&D and the corresponding Mills' ratio. Then one estimates a simple linear (OLS) for R&D intensity, adding to this equation the predicted probabilities from the R&D decision equation, the Mills' ratio, their squares and an interaction term between the predicted probabilities and Mill's ratio. The presence of selectivity bias is then tested for by looking at the significance of these "probability terms". The results for this test are reported as model (1) in Table C1 in the Appendix C. The predicted probability terms are jointly significant, with a $\chi^2(5)$ = 11.41. It therefore concludes that selection bias is present in my data on R&D and estimate the full two equation Heckman model by maximum likelihood (the first two columns of Table 3 or model (2) in Table C1). The results confirm the presence of selection with a highly significant estimated correlation coefficient ρ of almost

Table 3: Estimation Results - Sample Selection Model for R&D and ICT Choice (All Firms).

	(1) Selection R&D		(2) OLS	(3) Selection ICT		(4) OLS
Dependent variables	R&D>0	Log R&D per emp	Log R&D per emp	ICT>0	Log ICT per emp	Log ICT per emp
Log employment	0.104	-0.765***	-0.666***	0.518***	0.091*	0.091*
	[0.063]	[0.096]	[0.094]	[0.063]	[0.051]	[0.051]
Log employment squared	0.003	0.036***	0.030***	-0.043***	-0.010	-0.010
	[0.007]	[0.011]	[0.011]	[0.008]	[0.006]	[0.006]
Market location: National	0.331***	0.245***	0.312***	0.081**	0.153***	0.153***
	[0.035]	[0.052]	[0.051]	[0.036]	[0.026]	[0.026]
Market location: Indian	0.521***	0.461***	0.558***	0.041	0.198***	0.198***
	[0.053]	[0.068]	[0.066]	[0.061]	[0.045]	[0.045]
Market location: World	0.601***	0.702***	0.802***	-0.022	0.312***	0.312***
	[0.062]	[0.075]	[0.072]	[0.073]	[0.052]	[0.052]
Part of a group	-0.046	0.103**	0.101**	-0.077**	0.079***	0.079***
	[0.035]	[0.046]	[0.046]	[0.034]	[0.026]	[0.026]
Hampering factor: high costs	0.280***	-0.053**	-0.011	0.041**	-0.012	-0.012
	[0.018]	[0.023]	[0.022]	[0.020]	[0.013]	[0.013]
Hampering factor: staff	0.136***	0.084***	0.104***	0.028	0.046***	0.046***
	[0.021]	[0.022]	[0.022]	[0.025]	[0.016]	[0.016]
Hampering factor: information	0.111***	-0.023	-0.010	0.035	-0.018	-0.018
	[0.024]	[0.026]	[0.026]	[0.029]	[0.019]	[0.019]
Cooperation in innovation		0.241***	0.252***		0.188***	0.188***
		[0.039]	[0.039]		[0.031]	[0.031]
Received subsidies		0.719***	0.738***		0.137***	0.137***
		[0.041]	[0.041]		[0.032]	[0.032]
Positive investment history	1.732***			0.914***		
	[0.042]			[0.076]		
Chi-squared or F-test for age dummies		58.80***	0.51	20.23**		1.90*
Chi-squared or F-test for industry dummies		828.21***	20.30***	2419.54***		80.18***
Chi-squared or F-test for regional dummies		23.54**	2.43**	53.49***		8.13***
Chi-squared or F-test for time dummies		165.66***	2.29*	765.45***		237.19***
Correlation coefficient rho		-0.239***		-0,003		
Chi-squared for selection		27.17***		0.01		
R-squared		0.50	0.49	0.29		0.29
Number of obs.(uncensored)		14533(4377)	4377	14533(12982)		12982

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Wholesale industry (NACE 51), mature firms (16 years old or older) in the capital region (Delhi). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level. Estimated by maximum loglikelihood as a Heckman selection model.
*** P<0.01, ** P<0.05, * P<0.1

-0.24. As expected the R&D investment history variable is positive and highly significant for the propensity to invest in R&D indicating the extent of persistency in the firms' R&D policy. Not having much effect on other explanatory variables the inclusion of this variable in the selection equation, however, neglects the effect of firm size on the propensity to innovate what is a usual result in the CDM model literature (see also model (3) in Table C1 for comparison). This is probably due to the fact that larger firms invest more often in R&D than smaller firms. The inclusion of the Positive R&D history variable in the selection equation also changes the sign of the estimated correlation coefficient ρ between the regression error and selection error terms, hence, resulting in the opposite direction of selection bias (comparing model (2) and model (3) in Table C1). However, not including this variable together with the usage of the same explanatory variables both in the selection and R&D intensity equations (as in Hall et al. [11]) results in failure of the Heckman procedure to identify selection bias in the data (see model (4) in Table C1). This is possibly due to that my Received subsidies variable can differ from the one used in Hall et al. [11], who use this type of variable also in the selection equation for R&D. Their variable covers subsidies for investments in general, while my variable covers just subsidies for R&D resulting in 1:1 match of receiving subsidy and doing R&D and, hence, in extremely high estimated coefficient for the Received subsidies variable in the selection equation (see model (4) in Table C1). According to Stolzenberg and Relles [29] that can lead to extremely high correlation between predictors in the R&D intensity equation and Heckman correction and, hence, to the collinearity problems when the two-step selection correction is applied. Stolzenberg and Relles [29] also notice that a downward-biased estimate could be quite useful for testing a substantive hypothesis of a positive impact of the variable of interest (then one might reasonably conclude that one has found a lower-bound estimate of the corresponding coefficient). Keeping that in mind it uses model (2) in Table C1 as my basic specification, since this model gives the "lowest" estimated coefficients for the main predictors of R&D intensity.

The results for the other explanatory variables in the basic model specification (model (1) in Table 3) are in line with the previous results in the CDM model literature. The enterprise's international propensity (reflected by main product market location variables) is also positively correlated with the probability that the firm is engaged in R&D, confirming the close relationship between technological capabilities and export propensity that has previously been established in the literature [14]. Belonging to a group does not influence the propensity to invest in R&D. Finally, the regression results indicate a positive and significant relationship between the three hampering factor variables – high costs, lack of qualified personnel and access to information – and the propensity to engage in R&D. In line with the previous CDM works, this is interpreted as an indication of the relevance of these variables as factors shaping the innovative process.

Turning to the R&D intensity equation itself, one can first observe that not controlling for selection appears to result mainly in upward bias of the estimated coefficients, but does not have much effect on their significance (compare intensity equations in selection model (1) and OLS model (2) in Table 3). Similar to the propensity of doing R&D, R&D intensity increase with firm's international orientation, i.e., firms facing competitors for their main products/services at the national, or other international markets have much higher R&D intensities than firms selling their main products/services at the local/regional marked. Firms that are part of a group (better internal access to financial sources), who cooperate with other firms or universities/high schools in their innovative activities (larger scope of R&D projects), who receive subsidies for R&D and those with lack of qualified personnel is an important hampering factor (possibly have to purchase R&D from external providers) invest more intensively in R&D. At the same time R&D intensity falls with firm size and with importance of having high costs as a hampering factor. The former result is natural by construction of the dependent variable (R&D expenditures per employee). The latter result together with an increasing R&D intensity when getting subsidies suggests that financial frictions may be important for these firms.

For comparison to the R&D equation, it also estimates the corresponding selection and OLS models for ICT investment (see models (3) and (4) in Table 3). The specification is the same as for R&D investment with one exception, i.e., it uses a dummy for positive ICT capital lagged two years as a Positive investment history variable in the selection equation for ICT. As expected the reported bias or selection is not an important issue for this kind of investment, both because ICT is an instance of a 'general purpose technology' that can be easily bought, and is less plagued by uncertainty and less than R&D subject to a market failure, and also because ICT is more easily tracked. Hence, models (3) and (4) give identical results for the ICT intensity. Like R&D, ICT intensity increases with the enterprise's international orientation (communication possibilities become more important when a firm is engaged in foreign activities), but its impact on ICT intensity is lower. Group membership (better internal access to financial sources), cooperation in innovation and magnitude of hampering factor: lack of qualified staff (in both cases communication possibilities are vital) have also positive impact on ICT intensity. Interestingly, receiving subsidies (which are R&D investment subsidies) increases ICT investment on average by 14 per cent, probably due to the fact that more financial resources become available for other types of investment when a firm get subsidy for doing R&D. In contrast to R&D intensity, ICT intensity increases with firm size in Norwegian firms (in contrast to what has been found for Italian firms, see Hall et al. [11]). Both R&D and ICT intensities vary with firm age, industry and location and in time.

Based on the results of Table 3 that explores the selection issues of R&D and ICT reporting and following Hall et al. [11], in the next section of the paper it uses the predicted values of R&D intensity (the expectation of R&D intensity conditional on the other firm characteristics) and the reported values of ICT investment intensity to explain the propensity for different types of innovation and the number of patent applications. This approach is justified both by the evidence that there is reporting bias in R&D, but not in the ICT investment and by the observation that R&D is more difficult to measure, especially for smaller firms, because it often occurs as a by-product of other activities and may not be separately tracked. It further explores the possible endogeneity of the reported ICT intensity and check the robustness of the results by including the lagged ICT capital as an input in the innovation output equation, i.e., ICT capital in the start of the corresponding survey period; or by instrumenting and including the predicted values of ICT intensity variable (based on model (4) in Table 3), as Rogers [14] do.

(2) Estimation stage 2: Innovation output

Tabs. 4–6 report the results of estimation of innovation output equations (13) – (15) for different innovation proxies (probability of innovating for four types of innovation, probability of innovating for any innovation and number of patent applications) and for three different samples of the firms (all firms, firms in Manufacturing and firms in Services).

Table 4 focuses on the whole sample of the firms and probability of innovating as a proxy for innovation output. First, the model (13) for four different types of innovation (product, process, organisational and marketing innovation) is estimated as a quadrivariate probit, accounting for the mutual dependence of the error terms $\eta_{it}^{j}, j=1,2,3,4$. Independence of the error terms is rejected with a highly significant value of a Chi-squared test, i.e., $\chi^2(6)$ = 3504.38. All four innovation types have similar relationships to the main explanatory variables increasing strongly with R&D and ICT intensities, the share of high skilled and the firm size. The first three variables are relatively most important for product innovation, while firm size has highest impact on organisational innovation. In addition to the positive impact of ICT intensity on all types of innovation, not having any ICT investment at all is strongly negative for product, process and marketing innovation. However, these effects are substantially lower than the effects of R&D intensity and share of high skilled man-hours indicating that the latter two factors are relatively more important for innovation (this result is in line with those obtained by Hall et al. [11]). As for other explanatory variables, the cooperation with other firms or Universities/high schools at the national and Scandinavian level (for all types of innovation) and at the European level (for product innovation) together with purchase of R&D services from external providers are positively related to the propensity to innovate, suggesting that the external acquisition of knowledge from specialized service providers represents an important complementary strategy through which firms are able to improve their innovative performance. The latter result is in line with those obtained earlier on Norwegian data by Cappelen et al. [26], which show that firms collaborating with others in their R&D are more likely to be successful in their innovation activities and patenting.

Table 4: Estimation Results - Innovation Output: Probability of Innovating (All Firms)

Dependent variables:	(1) Four types of innovation^												(2) Any innovation~			
	Product			Process			Organisational			Marketing						
	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Btstr.S.e.
All firms (14533 observations, 8554 firms)																
Log R&D intensity (predicted)	0.895	***	0.043	0.541	***	0.041	0.246	***	0.039	0.387	***	0.038	0.836	***	0.043	0.041
Share of high skilled	0.694	***	0.084	0.036		0.082	0.245	***	0.082	0.277	***	0.076	0.500	***	0.076	0.072
Log ICT intensity	0.054	***	0.012	0.042	***	0.012	0.044	***	0.011	0.022	**	0.011	0.046	***	0.010	0.010
Zero ICT investment	-0.107	**	0.054	-0.123	**	0.053	-0.057		0.053	-0.110	**	0.048	-0.125	***	0.044	0.042
Log employment	0.565	***	0.063	0.317	***	0.062	1.141	***	0.059	0.345	***	0.055	0.749	***	0.059	0.051
Log employment squared	-0.014	*	0.007	0.000		0.007	-0.086	***	0.007	-0.016	***	0.006	-0.030	***	0.007	0.006
Cooperation: National	0.509	***	0.046	0.485	***	0.043	0.359	***	0.042	0.438	***	0.041	0.564	***	0.050	0.043
Cooperation:	0.178	**	0.073	0.300	***	0.064	0.225	***	0.060	0.230	***	0.061	0.335	***	0.100	0.093
Cooperation	0.130	*	0.074	-0.081		0.065	0.064		0.063	0.041		0.064	0.026		0.097	0.118
Cooperation: World	-0.089		0.085	-0.016		0.076	0.025		0.069	-0.001		0.070	0.198		0.121	0.130
Purchased R&D	0.520	***	0.044	0.362	***	0.042	0.214	***	0.040	0.208	***	0.041	0.622	***	0.052	0.048
Non-zero observations	4189			3118			3145			3748			6967			
rho21	0.523	***	0.015													
rho31	0.273	***	0.017													
rho41	0.532	***	0.014													
rho32	0.426	***	0.016													
rho42	0.375	***	0.015													
rho43	0.459	***	0.015													
Chi-square for all rho=0	3504.38	***														
Log likelihood	-24017.06												-7804.49			

Notes: All regressions include a constant, firm age, industry, location and time dummies. Reference group: Local/regional market location, year 2017, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level. Btstr.S.e. are bootstrap standard errors based on 100 replications.
^ Estimated by maximum loglikelihood as a quadrivariate probit model; ~ Estimated by maximum loglikelihood as a simple probit model.
*** $P<0.01$, ** $P<0.05$, * $P<0.1$

The same results are reflected by the simple probit model estimation of equation (14) for any type of innovation (see model (2) in Table 4). However; it presents these results in order to compare them with those in Hall et al. [11], since they use the model specification for any type of innovation as their main specification. In addition, it provides different robustness checks for this case. As it mentioned earlier it uses the predicted R&D intensity and observed ICT intensity at this stage of the analysis. On the one hand, using the predicted values instead of the observed values is a sensible way to instrument the innovative effort in the knowledge production function in order to deal with simultaneity problems between R&D and the expectation of innovative success. On the other hand, given the fact that the model is estimated in sequential stages, conventional standard error estimates will be biased. The last column of Table 4 presents standard errors from simple probit model for any type of innovation computed via a panel bootstrap. In general, one can see that using a bootstrap makes relatively little difference to the standard errors and the significance of the results.

In order to check for possible endogeneity of ICT intensity variable in the innovation output equation (since it uses the observed ICT intensity in period t), it first reestimates model (2) in Table 4 by using the ICT capital intensity lagged two years as an input ICT variable, $ictk_{t-2}$, i.e., the log of ICT capital per employee in the start of the corresponding survey period. Then I reestimate model (2) in Table 4 by instrumenting and including the predicted values of ICT intensity variable based on model (4) in Table 3 [14]. The results are presented in Table C2, where model (1) corresponds to the basic model with observed ICT investment intensity, model (2) corresponds to the use of lagged ICT capital intensity and model (3) corresponds to the use of the predicted ICT investment intensity. The usage of the lagged ICT capital intensity changes marginally the main results (compare model (1) to model (2) in Table C2). While the usage of the predicted ICT investment intensity together with predicted R&D intensity results in a substantial reduction of the impact of the R&D intensity variable and huge increase in the impact of the ICT intensity variable. It interprets these results as a manifestation of the limitations of instrumenting two somewhat similar variables using the same set of predictors what can lead to a multicollinearity problem in the innovation output equation. It further concludes that the potential endogeneity problems of the observed ICT intensity variable is not crucial for the results and proceed to analysis for different industries with my basic specification.

To explore the hypothesis that the importance of innovation modes can differ between industries, it estimates equations (13) and (14) separately for manufacturing firms and firms in Services. Table 5 reports the corresponding results. These results confirm earlier findings that ICT is relatively more important for product innovation in Manufacturing and for process innovation in Services [5]. The same is true for the cooperation in innovation. As to other explanatory variables, R&D intensity and workers' skills are also strongly associated with innovation both in Manufacturing and Services, with R&D being more important for the propensity to innovate in Services and skills being relatively more important in Manufacturing. Cooperation in innovation seems to be relatively more important for innovating in Manufacturing, while purchasing of R&D from external providers has higher impact on innovating in Services.

It is also checked for the robustness of these results with respect to the exclusion of a skill variable and with respect to the inclusion of an interaction term between R&D intensity and a skill variable (again in

Table 5: Estimation results - Innovation output: Probability of innovating (Manufacturing firms versus firms in Services).

Dependent variables:	Four types of innovation^												Any innovation ~			
	New product			New process			Organisational			Marketing						
	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Coeff.		S.e.	Btstr.S.e.
Manufacturing firms (6199 observations, 3386 firms)																
Log R&D intensity (predicted)	0.800	***	0.061	0.598	***	0.059	0.165	***	0.057	0.360	***	0.054	0.803	***	0.063	0.056
Share of high skilled	0.814	***	0.150	-0.038		0.154	0.389	***	0.149	0.453	***	0.138	0.780	***	0.143	0.129
Log ICT intensity	0.089	***	0.019	0.043	**	0.018	0.048	***	0.019	0.053	***	0.018	0.074	***	0.018	0.016
Zero ICT investment	-0.068		0.074	-0.286	***	0.075	-0.169	**	0.081	-0.050		0.070	-0.165	***	0.066	0.063
Log employment	0.708	***	0.103	0.419	***	0.096	0.971	***	0.090	0.433	***	0.087	0.812	***	0.096	0.084
Log employment squared	-0.032	**	0.012	-0.013		0.011	-0.073	***	0.010	-0.028	***	0.010	-0.040	***	0.012	0.010
Cooperation: National	0.504	***	0.064	0.484	***	0.059	0.419	***	0.059	0.467	***	0.057	0.567	***	0.071	0.069
Cooperation: Delhi	0.162	*	0.098	0.348	***	0.080	0.270	***	0.079	0.245	***	0.080	0.448	***	0.140	0.124
Cooperation: India	0.227	**	0.102	0.024		0.085	0.043		0.083	0.007		0.090	0.142		0.150	0.147
Cooperation: World	-0.184	*	0.109	-0.078		0.103	0.031		0.096	-0.109		0.097	0.249		0.221	0.202
Purchased R&D	0.490	***	0.058	0.299	***	0.056	0.206	***	0.054	0.248	***	0.055	0.663	***	0.068	0.066
Non-zero observations	2217			1590			1467			1848			3412			
Chi-square for all rho=0	1382.10	***														
Log likelihood	-11292.29												-3234.75			
Firms in Services (6145 observations, 3947 firms)																
Log R&D intensity (predicted)	0.953	***	0.063	0.457	***	0.060	0.316	***	0.058	0.378	***	0.058	0.812	***	0.062	0.061
Share of high skilled	0.592	***	0.104	0.083		0.102	0.221	**	0.108	0.169	*	0.097	0.385	***	0.096	0.083
Log ICT intensity	0.035	**	0.017	0.042	**	0.016	0.037	**	0.016	-0.001		0.015	0.026	*	0.015	0.015
Zero ICT investment	-0.153	*	0.091	0.061		0.085	0.043		0.088	-0.190	**	0.077	-0.118	*	0.073	0.065
Log employment	0.493	***	0.087	0.247	***	0.089	1.295	***	0.098	0.274	***	0.079	0.678	***	0.086	0.074
Log employment squared	-0.007		0.010	0.002		0.010	-0.100	***	0.011	-0.009		0.009	-0.026	***	0.010	0.008
Cooperation: National	0.451	***	0.071	0.430	***	0.068	0.275	***	0.066	0.413	***	0.066	0.523	***	0.077	0.075
Cooperation: Delhi	0.186		0.116	0.203	*	0.112	0.189	*	0.098	0.208	**	0.102	0.294	*	0.162	0.162
Cooperation: India	0.066		0.110	-0.148		0.107	0.095		0.102	0.095		0.098	-0.044		0.143	0.145
Cooperation: World	0.108		0.139	0.194	*	0.117	0.064		0.100	0.172	*	0.102	0.289	*	0.166	0.176
Purchased R&D	0.535	***	0.072	0.370	***	0.067	0.244	***	0.066	0.175	***	0.067	0.590	***	0.088	0.073
Non-zero observations	1827			1327			1330			1677			2997			
Chi-square for all rho=0	1749.67	***														
Log likelihood	-10356.82												3459.13			

Note: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Manufacture of food products and beverages (NACE17) for Manufacturing firms or Wholesale (NACE51) for firms in Services, mature firms (16 years old or older)) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level. Btstr.S.e. are bootstrap standard errors based on 100 replications.
^ Estimated by maximum loglikelihood as a quadrivariate probit model; ~ Estimated by maximum loglikelihood as a simple probit model.
*** $P<0.01$, ** $P<0.05$, * $P<0.1$

order to compare my results with those in Rogers [14], who do not use a skill variable and with those in Hall et al. [11], who check for importance of an interaction term on their sample of Manufacturing firms). The results by industry are presented in Table C3. The impacts of R&D and ICT intensities remain positive and highly significant irrespective of inclusion or exclusion of the skill variable. In contrast to Hall et al. [11] the inclusion of an interaction term does not show evidence for complementarity between skills and R&D intensity in Manufacturing, while the estimated effect of the interaction term is positive and highly significant in Services. The other estimated coefficients in the basic model are largely unchanged by the addition of these variables.

Finally, Table 6 reports the results by industry for estimation of equation (15) where another proxy of innovation output is used, i.e. the number of patent applications. While the introduced innovation types show the *variety* of innovative process in the firm, the number of patent applications reflects the *scope* of innovation process. Since numbers of patent applications are observed as integer numbers with many zero observations, one can model them as zero inflated count data and use pseudo maximum likelihood for the estimation. In this model it uses

Table 6: Estimation Results – Innovation Output: Number of Patent Applications (by Industry).

Sample:	All firms		Manufacturing		Services	
Log R&D intensity (predicted)	0.898***	[0.093]	0.419***	[0.120]	1.500***	[0.142]
Share of high skilled	1.656***	[0.219]	2.190***	[0.310]	1.159***	[0.307]
Log ICT intensity	0.086***	[0.030]	0.104***	[0.037]	0.077*	[0.046]
Zero ICT investment	0.408***	[0.158]	0.282	[0.174]	0.446*	[0.264]
Log employment	1.145***	[0.153]	0.663***	[0.238]	1.983***	[0.251]
Log employment squared	-0.031**	[0.016]	0.010	[0.022]	-0.108***	[0.026]
Cooperation: National	0.039	[0.088]	0.152	[0.104]	-0.074	[0.158]
Cooperation: Delhi	0.041	[0.101]	-0.018	[0.120]	0.158	[0.191]
Cooperation: India	0.241**	[0.104]	0.275**	[0.126]	0.187	[0.187]
Cooperation: World	0.176	[0.113]	0.217	[0.142]	-0.051	[0.207]
Purchased R&D	0.369***	[0.080]	0.339***	[0.097]	0.405***	[0.137]
Inflation (any innovation)	-35.659***	[2.977]	-5.598***	[1.912]	-53.474***	[3.156]
Log likelihood	-4724.486		-2694.006		-1726.743	
Alpha for NB vs Poisson specification	1.24		0.89		1.67	
Vuong test for zero inflated specification	8.38***		5.36***		5.09***	
Number of observations (non-zero)	14533(1467)		6392 (900)		6145(503)	

Note: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Manufacture of food products and beverages (NACE15) for Manufacturing firms or Wholesale (NACE51) for firms in Services, mature firms (16 years old or older) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level.
Estimated by pseudo maximum loglikelihood as a zero inflated negative binomial (NB) count data model.
*** $P<0.01$, ** $P<0.05$, * $P<0.1$

Table 7: Estimation Results – Productivity: With Any Innovation (by Industry).

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Probability of any	0.086***	0.052***	0.012*	0.081***	0.043***	0.012*	0.078***	0.045***	-0.015
innovation (predicted)	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.007]	[0.012]	[0.012]	[0.012]
Log ICT capital		0.107***	0.092***		0.117***	0.102***		0.110***	0.096***
per employee		[0.005]	[0.005]		[0.006]	[0.006]		[0.007]	[0.007]
Share of high skilled			0.472***			0.491***			0.520***
			[0.031]			[0.045]			[0.035]
Log non-ICT capital	0.097***	0.076***	0.086***	0.095***	0.078***	0.087***	0.097***	0.070***	0.081***
per employee	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Log employment	0.114***	0.102***	0.107***	0.095***	0.081***	0.088***	0.130***	0.116***	0.115***
	[0.020]	[0.019]	[0.019]	[0.024]	[0.023]	[0.022]	[0.026]	[0.025]	[0.024]
Log employment squared	-0.010***	-0.008***	-0.008***	-0.005*	-0.002	-0.003	-0.015***	-0.012***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
R-squared	0.24	0.28	0.30	0.29	0.34	0.36	0.16	0.21	0.24
Number of observations	14427			6162			6086		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Manufacture of food products and beverages (NACE15) for Manufacturing firms or Wholesale (NACE51) for firms in Services and for the whole sample, mature firms (16 years old or older)) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level.
*** $P<0.01$, ** $P<0.05$, * $P<0.1$

a binary indicator for any type of innovation, *inno*, as a main inflate variable, since only innovative firms can apply for a patent. In addition, the inflation equation includes firm age, industry and location, and time dummies, since one can expect higher/lower probability of applying for a patent for some age groups, regions and industries. It also uses a count model specification with negative binomial distribution, since the Poisson distribution imposes equality of the variance and the mean of the count data that is not the case for my patent applications data. As show the results in Table 6 the dispersion parameter alpha is far from zero, so negative binomial (NB) specification of count data model is preferable to Poisson specification. Vuong test compares the zero-inflated NB model to a standard NB model. With highly significant Vuong test it can rejects a standard NB model specification and conclude that the zero-inflated NB model is a proper count data model specification for my data.

Turning to the estimation results themselves, they are in line with the results for main variables for innovating, i.e., R&D intensity and workers' skills are strongly associated with patenting both in Manufacturing and Services, with R&D being more important for the patenting in Services and skills being relatively more important in

Manufacturing. ICT intensity has also a positive impact on patenting, but, again, this impact is substantially lower than the impacts of R&D intensity and share of high skilled man-hours. Interestingly, opposite to the results for innovating, the coefficient for zero ICT investment is positive and significant. However, when it re-estimates the model for patent applications with ICT capital lagged two years (see column (5) in Table C2), the ICT variables become insignificant, while re-estimation with the predicted values of the ICT intensity (see column (6) in Table C2) makes the ICT intensity highly significant and more important for patenting than the R&D intensity. Such instability in the results for the ICT variable indicates that one cannot draw strong conclusions on the impact of ICT on patenting, while the results for other explanatory variables are robust to different model specifications. The cooperation with other firms or Universities/high schools together with purchase of R&D services from external providers are also positively related to the number of patent applications, but in contrast to the results for innovating where cooperation at the national and Delhi level was important, the cooperation at the India and world level is more important for patenting.

(3) Estimation stage 3: Productivity

In the last part of the analysis it looks at the productivity impacts of innovation activities by using the OLS estimation procedure. Tabs. 7–8 show estimates of equation (16) by industry with and without measures of ICT capital intensity and skill variable (while Hall et al. [11] control for the ICT intensity in the productivity equation, Rogers [14] do not include any of these two variables at the last stage of the CDM model). One can see that when it proxies innovation with the predicted probability of any innovation conditional on R&D, ICT, and the other firm characteristics included in Table 4, it was found a positive effect of innovation on productivity, i.e., doing any kind of innovation increases productivity by approximately 8 percent independent on the estimation sample (columns 1 of Table 7). Nevertheless, when it includes the ICT capital intensity in the productivity equation (columns 2 of Table 7), the predicted probability of innovation activity loses its impact substantially. ICT investment per employee appears to be a much better predictor of productivity gains than the probability of innovation predicted by ICT and R&D investments. When it includes also skill variable, the ICT capital coefficient is slightly decreased, while the innovation coefficient becomes very low (but still significant) for Manufacturing firms and even insignificant for the whole sample or firms in Services (columns 3 of Table 7). The latter result is in line with those in Crepon et al. [1] who also observe a substantial decrease in the estimated elasticity of knowledge capital for manufacturing firms when including the skill variable in the productivity equation. These results indicate that both ICT and skills are important inputs to the firm productivity and should not be ignored when analyzing effects of innovations on productivity and economic growth.

Table 8 reports the results for the productivity analysis when the predicted number of patent applications per employee is used as a proxy for innovation. The estimated elasticities of the number of patent applications per employee are high and significant being about 0.80 for Manufacturing firms, 0.24 for firms in Services and 0.33 for the whole sample (columns 1 of Table 8). While the inclusion of ICT variable slightly reduces the impact of patent variable (columns 2 of Table 8), in case of an additional inclusion of the skill variable (columns 3 of Table 8) the patent variable losses (almost) all its significance with exception for Manufacturing firms where the corresponding elasticity remains to be positive, significant and relatively high (0.22 compared to 0.09 in Crepon et al. [1] for French Manufacturing firms) indicating that patenting is relatively more important for productivity increase in Manufacturing while skills are relatively more important in Services.

Finally, Table 9 presents the results (by industry) for production function where the skill variable is included and where the predicted propensities for the combinations of different innovation types are used as a proxy for innovation, first for all four types of innovation based on quadrivariate probit estimation of all four equations in (13) (columns 1 of Table 9) and then (in order to compare my results with earlier literature) for product, process and organisational innovation based on the trivariate probit estimation of the three first equations in (13) (columns 2 of Table 9). The results for all four types of innovation (columns 1) show that product innovation (alone or in combination with marketing innovation) is very important for the productivity in Manufacturing (coefficients for QP1000 and QP1001 are positive and highly significant even when the skill variable is included, while coefficient for QP0111 is negative and highly significant). While process and organisational innovations seems to be important for productivity in Services (coefficients for QP0100 and QP0010 are positive and highly significant even when the skill variable is included, while coefficient for QP1101 is negative and highly significant).

Table 8: Estimation Results – Productivity: with Number of Patent Applications Per Employee (by Industry).

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Number of patent appl.	0.331***	0.240***	-0.053	0.801***	0.606***	0.220**	0.240***	0.201***	-0.033
per empl. (predicted)	[0.059]	[0.057]	[0.056]	[0.098]	[0.093]	[0.096]	[0.066]	[0.064]	[0.063]
Log ICT capital		0.112***	0.093***		0.122***	0.104***		0.113***	0.095***
per employee		[0.005]	[0.005]		[0.006]	[0.006]		[0.007]	[0.007]
Share of high skilled			0.496***			0.475***			0.510***
			[0.031]			[0.045]			[0.034]
Log non-ICT capital	0.101***	0.077***	0.086***	0.101***	0.081***	0.087***	0.098***	0.070***	0.081***
per employee	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Log employment	-0.020	0.001	0.134***	-0.216***	-0.161***	-0.001	0.027	0.024	0.128***
	[0.036]	[0.034]	[0.032]	[0.045]	[0.043]	[0.043]	[0.041]	[0.040]	[0.039]
Log employment squared	0.004	0.003	-0.010***	0.028***	0.023***	0.006	-0.005	-0.003	-0.013***
	[0.004]	[0.004]	[0.003]	[0.005]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
R-squared	0.23	0.27	0.30	0.28	0.34	0.36	0.16	0.21	0.24
Number of observations	14427			6162			6086		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Manufacture of food products and beverages (NACE17) for Manufacturing firms or Wholesale (NACE51) for firms in Services and for the whole sample, mature firms (16 years old or older)) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level.

*** $P<0.01$, ** $P<0.05$, * $P<0.1$

Table 9: Estimation Results – Productivity: With Combinations of Different Innovation Types (by Industry).

	All firms				Manufacturing				Services			
Innovation types:	(1) pdt,pcs,org,mkt		(2) pdt,pcs,org		(1) pdt,pcs,org,mkt		(2) pdt,pcs,org		(1) pdt,pcs,org,mkt		(2) pdt,pcs,org	
QP1111 (predicted)	0.441**	[0.175]			0.096	[0.230]			0.375	[0.230]		
QP1110 (predicted)	0.907	[0.674]			0.694	[0.727]			1.368	[0.950]		
QP1101 (predicted)	-1.162***	[0.312]			-0.472	[0.417]			-0.868**	[0.364]		
QP1011 (predicted)	-0.296	[0.674]			0.974	[0.909]			-0.387	[0.802]		
QP0111 (predicted)	-1.569	[1.276]			-3.164**	[1.350]			-2.487	[1.848]		
QP0011 (predicted)	1.126	[0.888]			0.961	[1.139]			2.035*	[1.107]		
QP0101 (predicted)	1.449	[1.716]			3.059	[1.867]			-0.104	[2.107]		
QP0110 (predicted)	0.100	[0.871]			1.500	[1.044]			-0.410	[1.349]		
QP1001 (predicted)	1.713***	[0.472]			1.294**	[0.545]			0.974	[0.667]		
QP1010 (predicted)	-0.663	[1.089]			-3.232**	[1.456]			1.485	[1.542]		
QP1100 (predicted)	-1.178**	[0.504]			-1.323**	[0.663]			-0.589	[0.587]		
QP0001 (predicted)	-0.706	[0.475]			-0.647	[0.567]			-0.891	[0.563]		
QP0010 (predicted)	0.237	[0.299]			-0.455	[0.531]			0.685*	[0.396]		
QP0100 (predicted)	1.218*	[0.644]			-0.641	[0.583]			4.855***	[0.909]		
QP1000 (predicted)	0.503*	[0.278]			0.753***	[0.291]			-0.167	[0.417]		
TP111 (predicted)			0.454***	[0.106]			0.313**	[0.130]			0.245*	[0.137]
TP110 (predicted)			-1.075***	[0.164]			-0.559***	[0.189]			-0.671***	[0.209]
TP101 (predicted)			0.011	[0.305]			-0.269	[0.326]			0.835**	[0.363]
TP011 (predicted)			0.049	[0.438]			-0.274	[0.455]			0.300	[0.589]
TP001 (predicted)			0.164	[0.234]			-0.021	[0.319]			0.340	[0.283]
TP010 (predicted)			-0.238	[0.422]			-0.291	[0.394]			2.061***	[0.518]
TP100 (predicted)			1.186***	[0.194]			0.826***	[0.206]			0.277	[0.232]
ICT capital intensity	0.090***	[0.005]	0.091***	[0.005]	0.100***	[0.006]	0.101***	[0.006]	0.088***	[0.007]	0.092***	[0.007]
Non-ICT capital intensity	0.085***	[0.004]	0.084***	[0.004]	0.086***	[0.005]	0.086***	[0.005]	0.080***	[0.005]	0.080***	[0.005]
Share of high skilled	0.411***	[0.042]	0.357***	[0.040]	0.355***	[0.065]	0.376***	[0.062]	0.535***	[0.041]	0.521***	[0.041]
Log employment	0.075**	[0.034]	0.069**	[0.033]	0.088**	[0.039]	0.081**	[0.038]	0.034	[0.050]	0.054	[0.048]
Log employment squared	-0.006*	[0.003]	-0.005	[0.003]	-0.002	[0.004]	-0.002	[0.004]	-0.007	[0.005]	-0.007	[0.005]
R-squared	0.30		0.30		0.36		0.36		0.25		0.24	
Number of observations	14427		14427		6162		6162		6086		6086	

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Manufacture of food products and beverages (NACE15) for Manufacturing firms or Wholesale (NACE51) for firms in Services and for the whole sample, mature firms (16 years old or older)) in the capital region (Delhi). The standard errors are robust to heteroscedasticity and clustered at the firm level.

*** $P<0.01$, ** $P<0.05$, * $P<0.1$

5. CONCLUSION

Two measures of innovative output are tested, i.e., four types of innovation (product, process, organizational and marketing innovation) and number of patent applications. It was found that R&D and ICT are both strongly associated with innovation and productivity, with R&D being more important for innovation, and ICT being more important for productivity. These results suggest that ICT is an important driver of productivity growth that could explain the "Indian productivity puzzle", i.e., the feature that India having a relative low level of R&D intensity is one of the most productive countries. The results also indicate considerable differences between firms in Manufacturing and Services with respect to innovation and productivity effects of ICT, R&D and human capital.

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APPENDIX A. DATA SOURCES

R&D statistics: R&D statistics are the survey data collected by Statistics India every second year up to 2017 and annually later on. These data comprise detailed information about firms' R&D activities, in particular, about total R&D expenses with division into own-performed R&D and purchased R&D services, the number of employees engaged in R&D activities and the number of man-years worked in R&D. The 2009, 2011, 2013, 2015 and 2017 editions are combined with the Community Innovation Survey (CIS) and contain information on whether firms have introduced different types of innovation over the three-year period before each survey. In each wave the sample is selected with a stratified method for firms with 10-50 employees, whereas the firms with more than 50 employees are all included. Strata are based on industry and firm size. Each survey contains about 5000 firms (6000 in the most recent surveys), although not all of them provide complete information.

The patent data: This database contains data on the total number of the Indian patents applied for by the firm in the given year (available from 1990). These data are obtained by Statistics India from the Indian Patent Office and contain a firm identifier that allows merging them with other data sources.

The structural statistics: The term "structural statistics" is a general name for the different industrial activities statistics (e.g., Manufacturing statistics, Building and construction statistics, etc.), which are based on General Trading Statements, given in an appendix to the tax return. They all have the same structure and include information about production, input factors and investments at the firm level. Since 2002 this data comprise information on annual investments in hardware (purchased) and software (both purchased an own account). The structural statistics are organised according to the Standard Industrial Classification SN2002 (SN2007 since 2007) and are collected for the following industries (NACE-codes from SN2002 in brackets):

-Manufacturing (NACE 15-37)

-Building and construction (NACE 45)

-Wholesale and retail trade (NACE 50-52)

-Transport, storage and communication (NACE 60-64)

-Business related services (NACE 72-74)

-Other industries (NACE 5, 10-14, 40-41, 55, 59, 65-67, 90, 93).

Accounts statistics: In the accounts statistics, a firm is defined as "the smallest legal unit comprising all economic activities engaged in by one and the same owner" and corresponds in general to the concept of a company. A firm can consist of one or more establishments which are the geographically local units conducting economic activity within an industry class. Another unit is the consolidated group, which consists of a parent company and one or more subsidiaries. Both the parent company and the subsidiaries are firms as defined here. All joint-stock companies in Norway are obliged to publish company accounts every year. The accounts statistics contain information obtained from the income statements and balance sheets of joint-stock companies, in particular, the information about operating revenues, operating costs and operating result, labour costs, and the book values of the firm's tangible fixed assets at the end of a year, their depreciation and write-downs.

The Register of Employers and Employees (REE) contain information about each individual employee's contract start and end, wages and working hours. Containing both the firm identification number ant the personal identification number these data can easily be aggregated to the firm level.

Table A1: Correlation coefficients for firms with positive R&D (4147 observations).

	Log *Y/L*	Log *R/L*	Log *ICT/L*	*inno*	*sum-pat*	Log *L*	*h*	Market location	Part of a group	Receive subsidy	Coop.	Purch. R&D
logVAemp	1											
Log R&D intensity	0.09	1										
Log ICT intensity	0.28	0.31	1									
Dummy for innovation	-0.02	0.15	0.04	1								
No. of patent appl.	0.16	0.09	0.02	0.05	1							
Log employment	0.18	-0.44	-0.12	0.02	0.19	1						
Share of high skilled	0.22	0.49	0.45	0.02	0.06	-0.28	1					
Market location	0.09	0.21	0.04	0.07	0.15	0.08	0.09	1				
Part of a group	0.17	-0.15	-0.02	-0.02	0.05	0.39	-0.12	0.10	1			
Receive subsidy	-0.08	0.33	0.03	0.11	0.08	-0.08	0.10	0.09	-0.07	1		
Cooperation	0.05	0.09	-0.00	0.09	0.09	0.11	0.03	0.11	0.07	0.15	1	
Purchased R&D	0.05	0.03	-0.08	0.07	0.09	0.21	-0.12	0.14	0.12	0.09	0.30	1

The National Education Database (NED) includes individually based statistics on education and contains a six-digit number where the leading digit describes the educational level of the person. It used this data set to identify the length of education of employees. This information was first integrated into a common data base with REE and then aggregated to the firm level.

APPENDIX B. DEFINITIONS AND EXAMPLES OF DIFFERENT TYPES OF INNOVATION

The Delhi Manual defines an 'innovation' as:

"…the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organisation or external relations."

A product innovation is the introduction of a good or service that is significantly improved with respect to its characteristics or intended uses and includes significant improvements in technical specifications, components and materials, incorporated software and user friendliness or other functional characteristics. Design changes which do not involve a significant change in the product's functional characteristics or intended use, such as a new flavour or colour option, are not product innovations. Product innovations in services can include significant improvements in how the product is provided, such as home pick-up or delivery services, or other features which improve efficiency or speed.

A process innovation is a new or significantly improved production or delivery method, including significant changes in techniques, equipment

and/or software. For example, introduction of a new automation method on a production line, or in the context of ICT, developing electronic system linkages to streamline production and delivery processes, are both process innovations.

With respect to services, it is often difficult to distinguish a product and process innovation. The Delhi Manual contains the following guidelines to distinguish these two types of innovation:

• if the innovation involves new or significantly improved characteristics of the service offered to customers, it is a product innovation;

• if the innovation involves new or significantly improved methods, equipment and/ or skills used to perform the service, it is a process innovation.

An organisational or managerial innovation is the implementation of a new or significantly improved method of the firm's business practices, workplace organisation or external relations. It requires more than mere organisational change or restructure. In fact, the organisational method must not have been previously used by the business and must be the results of strategic decisions taken by management. Examples include implementation a new method for distributing responsibilities and decision making among employees, decentralising group activity, developing formal or informal work teams, new types of external collaboration with research organisations or the use of outsourcing or sub-contracting for the first time. A marketing innovation is the implementation of a new or significantly improved marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing. The marketing method must not have been previously used by the firm and must be part of a new marketing concept or strategy representing a significant departure from the firm's existing methods.

APPENDIX C. DIFFERENT ISSUES ON THE MODEL ESTIMATION.

Table C1. Estimation of sample selection model for R&D choice.

	(1)		(2)		(3)		(4)	
Dependent variables:	Probit R&D>0	OLS Log R&D per empl.	Selection R&D>0	model Log R&D per empl.	Selection R&D>0	model Log R&D per empl.	Selection R&D>0	model Log R&D per empl.
Log employment	0.096	-0.817***	0.104	-0.765***	0.429***	-0.624***	0.391***	-0.666***
	[0.063]	[0.096]	[0.063]	[0.096]	[0.070]	[0.094]	[0.075]	[0.094]
Log employment squared	0.004	0.038***	0.003	0.036***	-0.015*	0.028**	-0.015	0.030***
	[0.007]	[0.011]	[0.007]	[0.011]	[0.009]	[0.011]	[0.009]	[0.011]
H: high costs	0.283***	-0.095***	0.280***	-0.053**	0.340***	0.021	0.237***	-0.011
	[0.018]	[0.024]	[0.018]	[0.023]	[0.017]	[0.024]	[0.020]	[0.022]
H:lack of qualified personal	0.136***	0.064***	0.136***	0.084***	0.173***	0.120***	0.155***	0.104***
	[0.021]	[0.023]	[0.021]	[0.022]	[0.020]	[0.022]	[0.025]	[0.022]
H:lack of information	0.111***	-0.038	0.111***	-0.023	0.121***	0.001	0.091***	-0.010
	[0.024]	[0.027]	[0.024]	[0.026]	[0.022]	[0.026]	[0.028]	[0.026]
Market location: National	0.330***	0.203***	0.331***	0.245***	0.456***	0.358***	0.324***	0.311***
	[0.035]	[0.052]	[0.035]	[0.052]	[0.034]	[0.052]	[0.041]	[0.050]
Market location: India	0.523***	0.370***	0.521***	0.461***	0.739***	0.626***	0.577***	0.558***
	[0.054]	[0.070]	[0.053]	[0.068]	[0.054]	[0.069]	[0.063]	[0.066]
Market location: World	0.612***	0.591***	0.601***	0.702***	0.833***	0.875***	0.691***	0.802***
	[0.063]	[0.076]	[0.062]	[0.075]	[0.062]	[0.077]	[0.077]	[0.072]
Part of a group	-0.047	0.104**	-0.046	0.103**	-0.023	0.099**	-0.034	0.101**
	[0.035]	[0.046]	[0.035]	[0.046]	[0.034]	[0.046]	[0.041]	[0.046]
Cooperation in R&D		0.235***		0.241***		0.251***	1.361***	0.251***
		[0.039]		[0.039]		[0.039]	[0.049]	[0.039]
Received subsidies		0.711***		0.719***		0.738***	3.198***	0.737***
		[0.041]		[0.041]		[0.041]	[0.139]	[0.054]
Exclusion restriction:								
Positive R&D history	1.719***		1.732***					
	[0.042]		[0.042]					
No info. on R&D history	0.423***		0.438***					
	[0.045]		[0.045]					
Chi-square for selection		11.41***		27.17***		10.18***		0.00
Correlation coefficient rho				-0.239***		0.138***		-0.001
Log likelihood	-4581.74			-11294.48		-12496.10		-10362.24

Number of obs. (uncensored)	14533	4377	14533(4377)	14533(4377)	14533(4377)

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Delhi). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Models (2)-(4) are estimated by maximum loglikelihood as a Heckman selection model. Model (3) is similar to the model in Parisi et al. [3] and model (4) is similar to the model in Hall et al. [11].
*** P<0.01, ** P<0.05, * P<0.1

Table C2: Exploring endogeneity of ICT variable in the innovation output equation (all firms).

Innovation output:	Any type of innovation^			Number of patent applications~		
	(1)	(2)	(3)	(4)	(5)	(6)
ICT variable:	Observed ICT intensity	Lagged ICT intensity	Predicted ICT intensity	Observed ICT intensity	Lagged ICT intensity	Predicted ICT intensity
Log R&D intensity (predicted)	0.836***	0.842***	0.430***	0.898***	0.886***	0.421**
	[0.043]	[0.043]	[0.093]	[0.093]	[0.093]	[0.201]
Share of high skilled	0.500***	0.487***	0.535***	1.656***	1.618***	1.731***
	[0.076]	[0.077]	[0.075]	[0.219]	[0.220]	[0.219]
Log ICT intensity	0.046***	0.056***	1.173***	0.086***	0.058	1.658***
	[0.010]	[0.012]	[0.235]	[0.030]	[0.043]	[0.563]
Zero ICT	-0.125***	-0.114		0.408***	-0.639	
	[0.044]	[0.167]		[0.158]	[0.489]	
Log employment	0.749***	0.769***	0.340***	1.145***	1.144***	0.597**
	[0.059]	[0.060]	[0.104]	[0.153]	[0.165]	[0.264]
Log employment squared	-0.030***	-0.031***	-0.005	-0.031**	-0.033*	0.005
	[0.007]	[0.007]	[0.009]	[0.016]	[0.017]	[0.022]
Cooperation: National	0.564***	0.565***	0.477***	0.039	0.036	-0.102
	[0.050]	[0.051]	[0.053]	[0.088]	[0.090]	[0.094]
Cooperation: Delhi	0.335***	0.337***	0.321***	0.041	0.087	0.031
	[0.100]	[0.102]	[0.099]	[0.101]	[0.103]	[0.101]
Cooperation: India	0.026	0.033	0.023	0.241**	0.275***	0.220**
	[0.097]	[0.098]	[0.095]	[0.104]	[0.105]	[0.105]
Cooperation: World	0.198	0.180	0.187	0.176	0.220*	0.168
	[0.121]	[0.121]	[0.119]	[0.113]	[0.116]	[0.114]
Purchased R&D	0.622***	0.623***	0.643***	0.369***	0.360***	0.381***
	[0.052]	[0.053]	[0.052]	[0.080]	[0.083]	[0.082]
Log likelihood	-7830.1328	-7609.6193	-7816.435	-4724.49	-4604.62	-4726.01
Number of observations	14533	14164	14533	14533	14164	14533
Non-zero observations	6967	6808	6967	1467	1432	1467

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Delhi). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
^ Estimated by maximum loglikelihood as simple probit model; ~ Estimated by pseudo maximum loglikelihood as a zero inflated negative binomial count data model
*** P<0.01, ** P<0.05, * P<0.1.

Table C3: Robustness checks for inclusion of skill variable in the innovation output equation (by industry).

Dependent variable:	All firms			Manufacturing			Services		
Prob. of any innovation	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Log R&D intensity	0.878***	0.836***	0.773***	0.860***	0.803***	0.762***	0.850***	0.812***	0.685***
(predicted)	[0.042]	[0.043]	[0.049]	[0.061]	[0.063]	[0.070]	[0.062]	[0.062]	[0.077]
Interaction of predicted			0.169**			0.177			0.239***
R&D and skilled share			[0.068]			[0.146]			[0.089]
Share of high skilled		0.500***	-0.150		0.780***	0.125		0.385***	-0.559
		[0.076]	[0.274]		[0.143]	[0.571]		[0.096]	[0.365]
Log ICT intensity	0.055***	0.046***	0.048***	0.093***	0.074***	0.076***	0.031**	0.026*	0.029*
	[0.010]	[0.010]	[0.010]	[0.017]	[0.018]	[0.018]	[0.014]	[0.015]	[0.015]
Zero ICT	-0.113**	-0.125***	-0.116***	-0.127*	-0.165**	-0.159**	-0.120	-0.118	-0.108
	[0.044]	[0.044]	[0.045]	[0.066]	[0.066]	[0.066]	[0.073]	[0.073]	[0.073]
Log employment	0.781***	0.749***	0.742***	0.855***	0.812***	0.803***	0.711***	0.678***	0.673***
	[0.059]	[0.059]	[0.059]	[0.095]	[0.096]	[0.096]	[0.085]	[0.086]	[0.085]
Log employment squared	-0.032***	-0.030***	-0.030***	-0.041***	-0.040***	-0.039***	-0.029***	-0.026***	-0.028***
	[0.007]	[0.007]	[0.007]	[0.012]	[0.012]	[0.012]	[0.010]	[0.010]	[0.010]
Cooperation: National	0.567***	0.564***	0.566***	0.558***	0.567***	0.570***	0.536***	0.523***	0.519***
	[0.050]	[0.050]	[0.050]	[0.071]	[0.071]	[0.071]	[0.076]	[0.077]	[0.077]
Cooperation: Delhi	0.326***	0.335***	0.338***	0.440***	0.448***	0.449***	0.282*	0.294*	0.315*
	[0.101]	[0.100]	[0.100]	[0.138]	[0.140]	[0.140]	[0.164]	[0.162]	[0.162]
Cooperation: India	0.031	0.026	0.020	0.144	0.142	0.140	-0.038	-0.044	-0.056
	[0.097]	[0.097]	[0.097]	[0.149]	[0.150]	[0.151]	[0.145]	[0.143]	[0.144]
Cooperation: World	0.214*	0.198	0.196	0.272	0.249	0.247	0.300*	0.289*	0.285*
	[0.121]	[0.121]	[0.121]	[0.223]	[0.221]	[0.222]	[0.167]	[0.166]	[0.167]
Purchased R&D	0.627***	0.622***	0.626***	0.669***	0.663***	0.662***	0.597***	0.590***	0.601***
	[0.052]	[0.052]	[0.052]	[0.068]	[0.068]	[0.068]	[0.088]	[0.088]	[0.088]
Pseudo *R*-squared	0.2217	0.2243	0.2247	0.2376	0.2416	0.2418	0.1853	0.1875	0.1886
Log likelihood	-7830.13	-7804.49	-7800.69	-3251.76	-3234.75	-3233.96	-3468.72	-3459.13	-3454.74
Number of obs. (non-zero)	14533(6967)			6199(3412)			6145(2997)		

Notes: All regressions include a constant, dummies for firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2017, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Delhi). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level. Innovation output: any type of innovation. Estimated by simple probit model.
*** $P<0.01$, ** $P<0.05$, * $P<0.1$.