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Abstract:
Business innovation is an important driver of productivity growth. In this paper, I assess the importance of R&D and ICT investment for firm performance in the manufacturing and service industries. Explicitly, I use an extended version of the CDM model that treats ICT together with R&D as the main inputs into innovation and productivity, and test it on a large unbalanced panel data set based on the innovation survey for Norway. Four different types of innovation and the number of patent applications are used as innovation output measures. I find that ICT investment is strongly associated with all types of innovation in both sectors, with the result being strongest for product innovation in manufacturing and for process innovation in service industries. The impact of ICT on patenting is only positive in manufacturing. Overall, ICT seems to be less important than R&D for innovation, but more important for productivity. These results support the proposition that ICT is an important driver of productivity growth. Given the high rate of ICT diffusion in Norway, my results also contribute to explaining what is referred to as the 'Norwegian productivity puzzle', i.e. the fact that Norway is one of the most productive economies in the OECD despite having relatively low R&D intensity.

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

JEL classification: D24, L60, L80, O3

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Sammendrag

I OECDs rapport om norsk økonomisk utvikling (OECD, 2007) fremheves det såkalte norske paradokset: at Norge har en meget lav satsing på FoU i forhold til andre høyinntektsland, men likevel en av de høyeste per kapita-inntektene i verden, et av de høyeste produktivitetsnivåer i industrien, og en av de høyeste levestandarder. Rapporten viser også at skårene på ulike innovasjonsindikatorer for Norge ligger klart lavere enn gjennomsnittet for andre OECD-land. Det har blitt gjennomført flere studier for å belyse det norske produktivitetsparadokset (se for eksempel OECD, 2008; Castellacci, 2008; og nylig Asheim, 2012 og von Brasch, 2015). Disse studiene trekker frem følgende mulige forklaringer på paradokset: (i) landets næringsstruktur med den høye produktiviteten i råvarebasert industri; (ii) det at Norge har en av Europas høyeste andeler av personer med høyere utdanning; og (iii) det at innovasjonsindikatorer måles for snevert og FoU investeringer ofte underrapporteres av norske foretak.

Ingen av studiene nevner at Norge er et av de landene som har ligget lengst fremme når det gjelder intensiv bruk av Informasjons- og kommunikasjonsteknologi (IKT) og spredning av bredbåndsteknologi. I 2011 var også Norge ledende i elektronisk handel blant OECD-land (kilde: www.oecd.org, Key ICT Indicators). Samtidig viser flere empiriske studier på foretaksnivå (for eksempel, Bresnahan mfl., 2002; Brynjolfsson og Hitt, 2003 og Hempell, 2005) at IKT-investeringer bidrar til økt produktivitetsvekst, særlig når det utføres komplementære investeringer rettet mot organisasjonsmessige endringer og prosessinnovasjoner. Halvorsen (2006), som studerer produktivitetsutviklingen i norsk økonomi for perioden 1981–2003, finner at TFP-veksten i private tjenesteytende næringer var mye høyere på 1990-tallet enn på 1980-tallet. Den sterke veksten fortsatte i 2001–2003. Von Brasch (2015) viser videre at den sterkeste TFP-veksten i årene 1978–2007 har skjedd innenfor Varehandel, samtidig som Rybalka (2009) viser at foretakene i Varehandel var blant de mest kapitalintensive når det gjelder IKT-kapital i årene 2002–2006. Gitt at teknologisk utvikling er en av de sentrale faktorene bak den beregnede TFP-veksten, gir alle disse tallene en støtte for velkjente oppfatninger om at moderne løsninger innenfor distribusjon og bruk av IKT aktivt har bidratt til å endre produksjonsprosessene og ført til produktivitetsvekst i denne næringen og som følge av det i den norske økonomien som helhet.

I den foreliggende studien åpner jeg for at IKT sammen med FoU og høykvalifisert arbeidskraft er sentrale forklaringsfaktorer både for innovasjon og produktivitet. Mer presist ser jeg på hvilken effekt IKT-investeringer har på foretakenes tilbøyelighet til innovasjoner i form av nye produkter, prosesser, organisasjonsmessige endringer og nye markedsføringsmetoder, samt deres utvikling mht. patentsøkning og arbeidsproduktivitet. Dette gjør jeg ved å bruke data fra Innovasjonsundersøkelsene i perioden 2004–2010 i kombinasjon med en utvidet versjon av CDM-modellen (Crepon mfl., 1998, Polder mfl., 2009 og Hall mfl., 2013). Studien inneholder også en sammenlignende analyse av betydningen av IKT for innovasjonsresultater og produktivitet i industri og tjenesteytende næringer. Jeg finner at IKT investeringer per ansatt har en klart signifikant effekt på tilbøyeligheten til alle typer innovasjoner. Den sterkeste effekten er på produktinnovasjon i industri og prosessinnovasjon i tjenesteytende næringer. Kun for industrien finner jeg en positiv sammenheng mellom IKT og antall patenter som foretaket har søkt om. Også arbeidskraftens sammensetning, målt ved andelen ansatte med høy utdanning, gjør foretaket mer innovativt og produktivt, alt annet likt. Foretakets IKT-kapitalintensitet spiller også en positiv rolle for produktiviteten og effekten er betydelig sterkere for produktivitet enn for innovasjon. Dette resultatet viser at IKT er en viktig faktor bak produktivitetsvekst og at høye norske IKT-investeringer bidrar betydelig til å forklare det såkalte norske paradokset.

1. Introduction

Business innovation is regarded as a potentially important driver of productivity growth, both at the firm and 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. At the macro level, strong business innovation increases multifactor productivity, thus increasing international competitiveness, economic growth and real per capital incomes.[1] It is therefore of great interest to businesses and policy-makers to identify the factors that stimulate innovation and to understand how these factors interact. R&D is an important factor behind innovations, but it is not the only one. Today, firms invest in a wide range of intangible assets, such as data, software, patents, new organisational processes and firm-specific skills. Together, these non-physical assets make up a firm's *knowledge-based capital*, KBC (see OECD, 2013). A lack of proper control for intangible assets and underinvestment in KBC are seen as the main candidates for explaining the poor productivity performance of European countries relative to the USA.[2] The need for Europe to move into the *knowledge-based economy* and support investment in KBC has been an important focus of government policy in European countries (see OECD, 2013).

Recently, more and more attention has been devoted to the role of Information and Communication Technology (ICT) as an enabler of innovation (see, for instance, Vincenzo, 2011). ICT is one of the most dynamic areas of investment, as well as a very pervasive technology.[3] The possible benefits of ICT use to a firm include among others increased input efficiency, general cost reductions and greater flexibility in the production process. This technology can also stimulate innovation activity in a firm, leading to higher product quality and the creation of new products or services. Its use has the potential to increase innovation by improving possibilities for communication 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 centralised management, leading to organisational innovation. Previous analyses confirm that ICT plays an important role in firm performance, *e.g*. Brynjolfsson and Hitt (2000, 2003), OECD (2004), Gago and Rubalcaba (2007), Crespi *et al.* (2007) and van Leeuwen (2008). These studies evaluate the effects of

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[1] See, for instance, Crépon *et al.* (1998), Griffith *et al.* (2006) and Parisi *et al.* (2006) for the studies at the micro level, and van Leeuwen and Klomp (2006) for the study at the macro level.

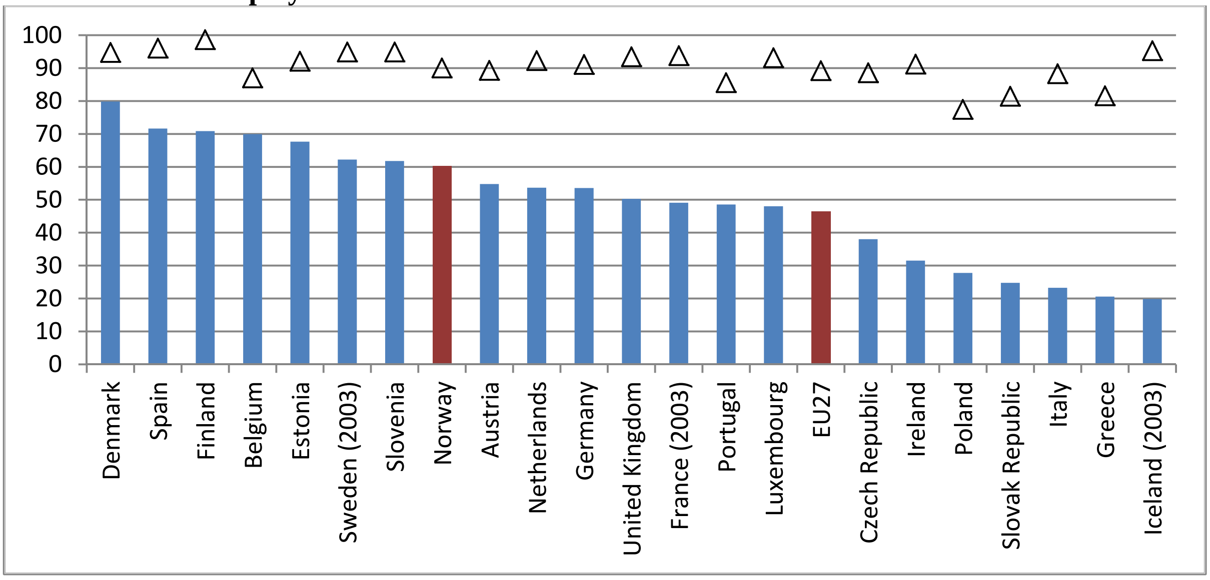
[2] See, for instance, van Ark *et al.* (2003), O'Sullivan (2006), Moncada-釘Paternò-Castello *et al.* (2009), Hall and Mairesse (2009) and Hall *et al.* (2013).

[3] ICT is often referred to as a modern general purpose technology, GPT (see Bresnahan and Trajtenberg, 1995, for a definition of GPT, and Castilione, 2012, for an investigation of GPT features of ICT).

ICT use and innovation on productivity. A few recent studies, i.e. Hall *et al.* (2013), Vincenzo (2011) and Polder *et al.* (2009), 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 Norwegian firms and to assess its relative importance for innovation and productivity compared to R&D. 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. I also use a count of patent applications as an alternative measure of innovative activity in firms.

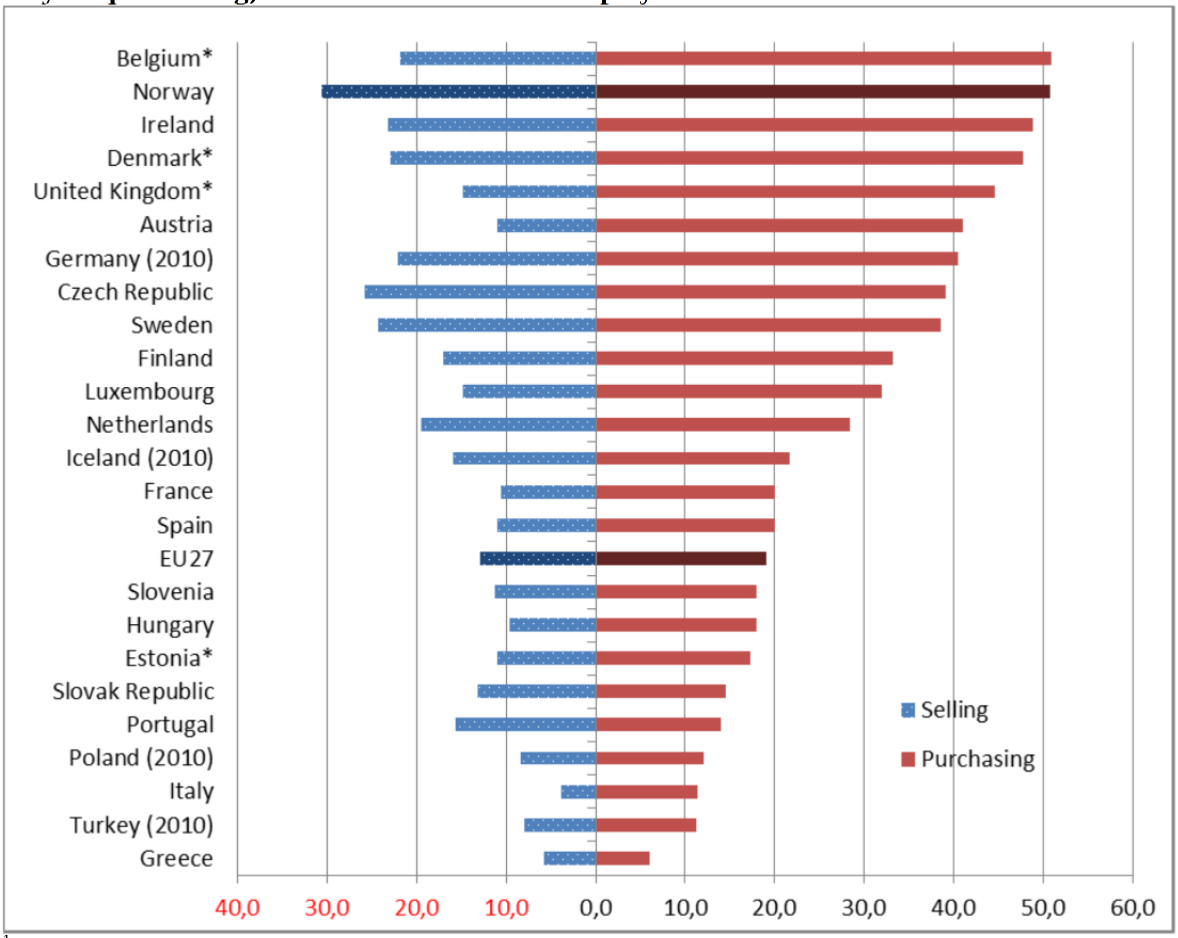
Figure 1. Share of firms with access to broadband in 2004 or 2003 (bars) and in 2011 (Δ). Firms with 10 or more employees



Source: www.oecd.org, Key ICT Indicators

Another aim of the study is to investigate whether a high level of ICT diffusion in Norway could explain the so-called 'Norwegian puzzle', i.e. the fact that, while R&D spending in the Norwegian business sector as a share of GDP is below the OECD average, the productivity performance of Norwegian firms is among the strongest in the OECD (see OECD, 2007). Several studies endeavour to explain the 'Norwegian puzzle' (also referred to as the Norwegian productivity paradox). OECD (2008) points to the skill level of the adult population and financial support from the public sector as positive factors behind Norway's strong productivity performance. On the other hand, they find weak innovation activity in the manufacturing sector. Castellacci (2008) claims that the source of the Norwegian productivity paradox lies in the sectoral composition of the economy. Recently, Asheim (2012) discussed 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. While providing several possible explanations for the 'Norwegian puzzle', none of these studies mention the high level of diffusion of ICT in Norway. For example, 60.3 per cent of Norwegian firms had access to broadband already in 2004, while the average for EU27 at that time was 46.5 per cent (see Figure 1). Also in 2011, when most European firms had access to broadband (the average for EU27 was 89.2 per cent), Norway was one of the leading European countries in e-commerce (see Figure 2 and OECD, 2011). This fact is one of the reasons why the current paper directs the attention to data on Norwegian firms. What is the relative importance of ICT for productivity compared to other key inputs, such as R&D and human capital, in a country with a high rate of ICT diffusion? Are they complements or substitutes?

Figure 2. Internet selling and purchasing[1] in all industries in 2011 (2010 when indicated, * 2010 only for purchasing). Firms with 10 or more employees



[1] Most countries explicitly use the OECD concept of internet commerce, that is, goods or services that are ordered over the internet, but where payment and/or delivery may be off line.
Source: www.oecd.org, Key ICT Indicators

To investigate these research questions, I apply the currently most used model for analysing the link between innovation input, innovation output and productivity, the so-called CDM model (Crepon *et al*., 1998). The standard version of the CDM model is a structural model that studies the following interrelated stages of the innovation chain: the choice by a firm of 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 impact of innovation output on the productivity of the firm. In the spirit of Polder *et al.* (2009) and Hall *et al.* (2013), I rely in this paper on an extended 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.* (2013) base their study on manufacturing firms alone, Polder *et al.* (2009) compare manufacturing firms with firms in services. Such comparison seems to be of substantial importance.

If we check the development of total factor productivity (TFP) in different industries in Norway in the three last decades compared to the USA,[4] we will see that most changes have taken place in the Wholesale and retail trade sector (see Figure 3). While the productivity level in the manufacturing sector remained between 60 and 70 per cent below the corresponding productivity level in the USA during the period 1978–2007, the Wholesale and retail trade sector showed a great increase in relative TFP, and, by 2007, it had almost reached the US level. At the same time, the Wholesale and Retail trade industries (when studied at the more detailed industry level) are among the most ICT capital-intensive industries in Norway (see Table 3 in Rybalka, 2009), i.e. the average share of ICT capital services in total capital services in 2002–2006 was 26.8 per cent for the Wholesale and 17.4 per cent for the Retail trade (the corresponding share for manufacturing is just 5.7 per cent).[5] Hence, it is very important to account for industry heterogeneity when studying the effects of ICT. In order to account for such heterogeneity, I present 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 'Norwegian puzzle' in previous studies, I also take into account the skill level of employees in Norwegian firms when analysing the effects of R&D and ICT on innovation and productivity.

Beyond presenting results for the Norwegian economy, this paper contributes to the existing literature in several ways. Firstly, I take into account the *pervasiveness* of ICT and treat it in parallel with R&D as a main input into innovation, rather than simply as an input into the production function. Secondly, in order to account for industry heterogeneity, I provide separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). Thirdly, I include marketing innovation in the analysis in addition to earlier investigated product, process and organisational

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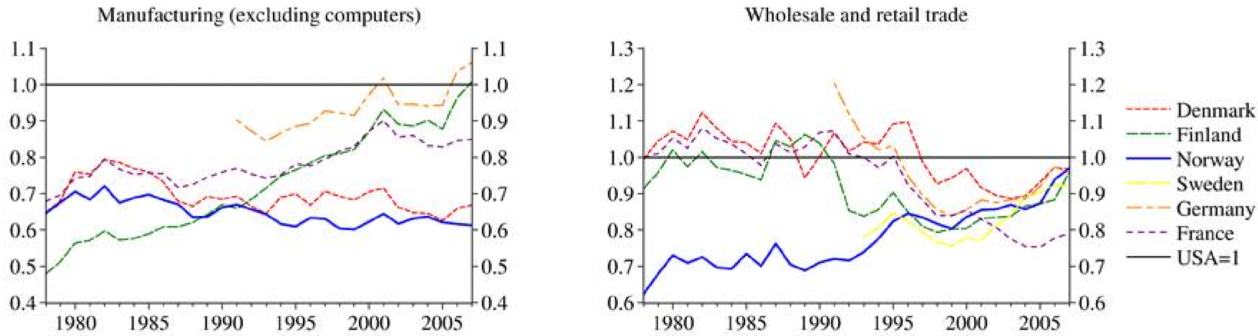
[4] Since US productivity has grown faster than productivity in Europe, the USA is often used as a reference country when studying productivity development in European countries, see, e.g., van Ark *et al.* (2003) and Aghion *et al.* (2009).

[5] This measure of ICT capital services is constructed on the basis of information about firms' investments in hardware and software collected by Statistics Norway since 2002 (for details of the construction procedure, see Rybalka, 2009).

innovation. All four types of innovation are equally represented in the data, which makes it possible to analyse the whole set of innovation types and enables a better understanding of the innovation process in the firm. Finally, I use the number of patent applications as an alternative measure for innovation. While the combination of different innovation types shows the *variety* of innovative processes in a firm, the number of patent applications reflects the *quality* of the innovation, i.e. only the best innovative products are expected to be protected by patent.

Figure 3. TFP levels in Manufacturing and the Wholesale and retail trade from 1978–2007 in some European countries relative to the US industry equivalents[1]



[1] All monetary measures for different countries are calculated in 1997 prices and USD using industry-specific Purchasing Power Parities from EU-KLEMS data (for details, see von Brasch, 2015).
Source: von Brasch (2015) based on OECD and EU-KLEMS data

For the analysis, I use a rich firm-level data set based on the four recent waves of the *Community Innovation Survey* (CIS) for Norway (CIS2004, CIS2006, CIS2008 and CIS2010), which contains information on different firms' innovative activities. By supplementing these data with information on the number of patent applications from the Norwegian patent database and on ICT investment and other relevant information from different registers, I obtain an unbalanced panel of 14 533 observations of 8 554 firms. The estimation results indicate considerable differences between firms in manufacturing and service industries with respect to innovation and the productivity effects of R&D and ICT. While ICT investment is strongly associated with all types of innovation in both sectors, with the result being strongest for product innovation in manufacturing and for process innovation in service industries, the impact of ICT on patenting is only positive in manufacturing. The estimation results also 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, together with human capital, should be taken into account when trying to explain the 'Norwegian productivity puzzle'.

The paper is organised as follows. Section 2 summarises the main findings from previous studies and explains the extended version of the CDM model. Section 3 presents the data set, the main variables and some descriptive evidence. Section 4 discusses the estimation of the empirical model, and Section 5 presents the results. Finally, Section 6 concludes.

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 quantify the role of ICT assets in firm performance in the form of productivity was made by Brynjolfsson and Hitt (1995). Since then, a broad range of empirical studies has emerged exploring the impacts of ICT on firm performance.[6] Most of these studies employ a production function framework to estimate the elasticity of output with respect to ICT capital, controlling for other factors, including innovations. However, very few of them focus on the direct link between ICT use and innovation.

As Koellinger (2005) 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 communicate effectively and collaborate across wider geographic areas will encourage strategies for less centralised 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, 2004). By enabling closer communication and collaboration, ICT helps businesses to be more responsive to innovation. For example, having broadband internet, a web presence and automated system linkages helps businesses to keep up with customer trends, monitor competitors' actions and get rapid user feedback, thereby helping them to exploit opportunities for all types of innovations.

Gretton *et al.* (2004) suggest the following two reasons why businesses' use of ICT encourages innovative activity. Firstly, ICT is a 'general purpose technology' that provides an 'indispensable

[6] See, for example, studies by Atrostic and Nguyen (2002), Biscourp *et al.* (2002), Bresnahan *et al.* (2002), Brynjolfsson and Hitt (2003), Crespi *et al.* (2007), Hall *et al.* (2013), Hempell (2005) and OECD (2004).

platform' upon which further productivity-enhancing changes, such as product and process innovations, can be based. For example, a business that 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 use, such as network economies, can be sources of productivity gains. For example, staff of businesses that have adopted broadband internet are able to collaborate more closely with wider networks of academics and international researchers 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 the main candidates for explaining the differences in productivity growth that are observed between Europe and the USA (for a comparative analysis of productivity growth in Europe and the USA, see, e.g., van Ark *et al.*, 2003; O'Sullivan, 2006; Moncada-Paternò-Castello *et al.*, 2009; and Hall and Mairesse, 2009). It is also true that firms' total R&D and ICT investments measured as shares of GDP are lower in Europe than in the United States and that the ICT gap is somewhat larger than that for R&D (see Figure 1 in Hall *et al.*, 2013). Hall *et al.* (2013) report so high rates of return on both ICT and R&D investments for Italian firms that they suspect considerable underinvestment in both these activities.

Another line of literature investigates the importance of ICT for firms' organisation (see Brynjolfsson and Hitt, 2000, for a survey and Bloom *et al.*, 2009, for a recent study). Case studies show that the introduction of information technology is combined with a transformation of the firm, investment in intangible assets, and changes in relations 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 of flexible production: just-in-time inventory management, integration of sales with production planning etc.

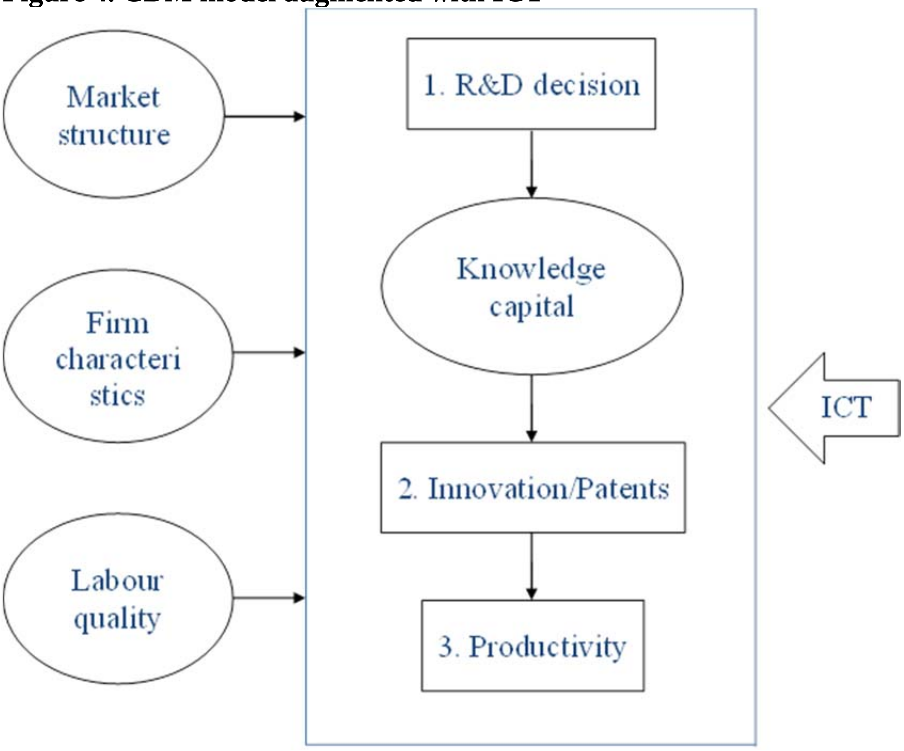
The available microeconometric evidence shows that a combination of investment in ICT and changes in organisations and work practices facilitated by these technologies contributes to firms' productivity growth. For instance, Crespi *et al.* (2007) use Innovation survey data for the UK and find a positive effect on firm performance of the interaction between ICT and organisational innovation. Gago and Rubalcaba (2007) find that businesses that invest in ICT, particularly those that regard their investment as strategically important, are significantly more likely to engage in services innovation. Van Leeuwen (2008) shows that e-sales and broadband use significantly affect productivity through their effect on innovation output. However, broadband use only has a direct effect on productivity if R&D is not considered as an input to innovation. This approach is further developed by Polder *et al.* (2009). 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. Cerquera and Klein (2008), in contrast, find that more intense use of ICT brings about a reduction in R&D efforts in German firms. The results for nine OECD countries in Vincenzo (2011) 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 no evidence that ICT-intensive firms have greater capacity to introduce ‘more innovative’ (new-to-the-market) products, suggesting that ICT enables the adoption of innovation rather than the development of new products. For Italian manufacturing firms, Hall *et al.* (2013) find that ICT investment intensity is associated with product and organisational 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 as regards the impact of ICT on innovation. In addition, very few papers have investigated these effects separately for manufacturing and services. Hence, more evidence is needed.

2.2 Modelling framework

The currently most used model for analysing the link between innovation input, innovation output and productivity is called the CDM model (Crepon *et al.*, 1998). It was applied, for instance, in Lööf and Heshmati (2002), Parisi *et al.* (2006) and van Leeuwen and Klomp (2006). The standard version of the model contains three different blocks: (1) First, the firm decides whether or not to invest in R&D; and how much to invest, if it chooses to do so; (2) second, the innovative input leads to the innovative output (e.g. product or process innovation, new technology, organisational change); (3) finally, the innovative output leads to increased labour productivity. Several recent studies have modified the standard CDM model in order to include other factors than R&D in the knowledge production function. For example, Castellacci (2011) uses the CDM model to investigate the effects of industry-level competition on firms’ innovation and productivity for Norway, while ICT is implemented in the CDM model by Griffith *et al.* (2006) for four European countries (France, Germany, Spain and the UK), Polder *et al.* (2009) for the Netherlands and by Hall *et al.* (2013) for Italy. These extensions of the standard model specification lead to extra difficulties in the estimation of the model, owing to the increased number of equations with qualitative dependent variables, for instance, when using different innovation types as a measure of innovative output. However, it is possible to bypass some of these difficulties by estimating the different blocks of the model sequentially.[7]

In this paper, I follow Polder *et al.* (2009) and Hall *et al.* (2013) and use an extension of the standard CDM model that analyses the effects of ICT on different stages of the innovative process. This version of the extended CDM model is presented in Figure 4. While Polder *et al.* (2009) use ICT as an additional input in the knowledge production function, but not in the production function, in Hall *et al.* (2013), the ICT investment is an input both in the production function and in the knowledge production function. While the former is in line with the more traditional view that ICT leads to productivity gains (e.g. through implementing new work practices and, hence, cost reductions and/or improved output); the latter introduces a less traditional view, i.e. that ICT may also stimulate innovation activity in the firm by speeding up the diffusion of information, promoting networking among firms, enabling closer links between businesses and customers, and leading to the 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. In this paper, I apply the model extension used in Hall *et al.* (2013). A more detailed description of different blocks of the model follows below.

Figure 4. CDM model augmented with ICT



[7] Note that this estimation strategy requires bootstrapping of standard errors, which I provide for some of the models.

Block 1: R&D input decision

This block does not differ from the first part of the standard CDM model. It models firm *i*'s decision to engage in R&D activities in period *t*. First the firm decides whether or not to start to invest in R&D in the given period; if it decides to invest, the firm then sets the amount of R&D investments. This statement of the problem can be modelled with a standard sample selection model (see Heckman, 1979):

(1) $$rd_{it} = \begin{cases} 1 & \text{if } rd^*_{it} = x^{rd}_{it}\alpha_1 + e_{it} > c \\ 0 & \text{else} \end{cases},$$

where rd_{it} is the observed binary endogenous variable equal to zero for non-R&D and one for R&D-performing firms, rd^*_{it} is a corresponding latent variable that expresses some decision criterion, such that a firm decides to invests in R&D if rd^*_{it} is above a certain threshold *c*, x^{rd}_{it} is a vector of firm characteristics (e.g. size, age, international orientation etc., and a constant term), α_1 is the associated coefficient vector, and e_{it} is an error term.

Once a firm has decided to engage in R&D activities, it must set the amount of resources devoted to R&D investments. Analogous to the previous equation and in line with the standard formulation of the CDM model, the latent R&D intensity of a firm *i* in a given period *t*, r^*_{it}, is represented as a function of another set of firm characteristics, x^r_{it}:

(2) $$r^*_{it} = x^r_{it}\alpha_2 + \varepsilon_{it} ,$$

where α_2 is the associated coefficient vector, and ε_{it} is an error term. The observed R&D intensity, *r*, is then equal to:

(3) $$r_{it} = \begin{cases} r^*_{it} & \text{if } rd_{it} = 1 \\ 0 & \text{else} \end{cases}$$

The pair of random disturbances e_{it} and ε_{it} is assumed to be jointly i.i.d. normally distributed, with zero mean and covariance matrix given by

(4) $$\begin{pmatrix} 1 & \rho\sigma_\varepsilon \\ \rho\sigma_\varepsilon & \sigma^2_\varepsilon \end{pmatrix},$$

where σ_e and σ_ε are the standard errors of e_{it} and ε_{it}, $\sigma_e = 1$ by standardisation, and ρ is their correlation coefficient. This model can be estimated by maximum likelihood.

Block 2: Innovation output

Let us now consider a model of how innovation occurs. R&D efforts lead to innovation output. Let $INNO^*$ be a latent variable that measures the extent of creativity/research activity within the firm. The higher the value of $INNO^*$, the higher is the probability that an innovation will occur. This modelling framework is influenced by Griliches (1990), Crepon *et al.* (1998) and Parisi *et al.* (2006). 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. An extended version of the CDM model also includes an ICT intensity, *ict*, together with R&D intensity, *r*, in the knowledge production function:

(5) $$INNO_{it}^* = \delta_1 \cdot r_{it} + \delta_2 \cdot ict_{it} + x_{it}^{inno}\beta + \eta_{it}$$

where x_{it}^{inno} is a vector of different firm characteristics important for innovation output (e.g. firm size, industry, cooperation in R&D projects etc., and a constant term), δ_1, δ_2 and β are parameters (vectors) of interest, and η_{it} is an error term.

The previous empirical studies based on the CDM model use different innovation output measures to proxy unobserved knowledge, $INNO_{it}^*$, e.g. the share of innovative sales (applied, for example, in Crepon *et al.*, 1998, and Castellacci, 2011); different binary innovation indicators (applied, for example, in Griffith *et al.*, 2006, for product and process innovation; in Polder *et al.*, 2009, for product, process and organisational innovation; and in Hall *et al.*, 2013, for product, process and two types of organisational innovation); and patent applications counts (applied, for example, in Crepon *et al.*, 1998). In this paper, I estimate equations for the following measures of innovation output in the second model block: (i) the probability of any innovation; (ii) the probability of four different types of innovation (product, process, organisational and marketing innovation); and (iii) the expected number of patent applications. In the first case, an equation for the binary indicator of any innovation is estimated as a *probit* model. In the second case, a system of four equations for binary indicators of corresponding types of innovation is estimated as a *quadrivariate probit* model, accounting for the mutual dependence of the error terms. In the latter case, since numbers of patent applications are observed as integer numbers with many zero observations, they are modelled by *zero-inflated count* *data model* (see Chapter 18.4.8 in Greene, 2011, for a description of the model and Aghion *et al.*, 2009, for the application of the zero-inflated count data model to the patent data).[8] Note that the variables for R&D intensity, r, and ICT intensity, ict, are endogenous because these investments are simultaneously determined with innovation activities. I discuss this issue in more detail under empirical model estimation in Section 4.

Block 3: Production function

The final block of the CDM model focuses on the effects of innovation output on labour productivity. In order to incorporate a firm's ICTs in the last block of the standard CDM model, I follow Hempell (2005) and use a traditional Cobb-Douglas production function with labour and two types of capital as inputs:

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

In (6), Y_{it} is the output of firm i in period t, measured as value added in constant prices, K_{it} and $ICTK_{it}$ are the corresponding amounts of tangible and ICT capital inputs in constant prices, L_{it} is the labour input, and A_{it} is total factor productivity (TFP). The parameters γ_1, γ_2 and γ_3 correspond, respectively, to output elasticities of the two types of capital and labour, and TFP is assumed to be determined by:

(7) $$\ln(A_{it}) = \pi_0 + INNO_{it}\pi_1 + x_{it}^{p}\pi_2 + \zeta_{it} .$$

In (7), $INNO_{it}$ is a vector of innovation output variables and x_{it}^{p} is a vector of different firm characteristics important for productivity (for instance, firm size, age and location); π_0, π_1 and π_2 are parameters (vectors) of interest and ζ_{it} is a white noise error term that comprises measurement errors and firm-specific productivity shocks. Dividing by L_{it} and taking logarithms on both sides of (6) yields:

(8) $$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 l_{it} + INNO_{it}\pi_1 + x_{it}^{p}\pi_2 + \zeta_{it} ,$$

[8] In this model, the zero outcomes can arise from one of two regimes, i.e. in one regime the outcome is always zero, and in the other, the usual count data generating process applies. Then, in the first step, the *inflation* equation that models the probability of falling in regime one is estimated by probit, and, in the second step, the standard count data generating process is estimated conditional on the outcome of the first step of estimation. I use a binary indicator for any type of innovation as a main *inflate* variable, since I expect that only innovative firms can apply for a patent. In addition, the inflation equation includes firm age, industry and location, and time dummies.

where $\breve{\gamma}_3 = (\gamma_1 + \gamma_2 + \gamma_3 - 1)$ and the small letters *lp*, *l*, *k* and *ictk* denote the logarithm of labour productivity, *Y/L*, labour input, *L*, tangible capital intensity, *K/L*, and ICT capital intensity, *ICTK/L*, correspondingly.[9]

I also allow 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, I decompose 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).[10] Letting N_h and N_l denote the corresponding amounts of man-hours (where the 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:

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

where $h_{it} = N_{h,it} / N_{it}$ denotes the share of hours worked by high-skilled workers in the firm. Taking the logarithm of (9) and inserting the expression for l_{it} into (8) yields:

(10) $$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 n_{it} + \gamma_4 h_{it} + INNO_{it}\pi_1 + x_{it}^{p}\pi_2 + \zeta_{it},$$

where the approximation follows from $\ln(1+\theta h_{it}) \approx \theta h_{it}$ and $\gamma_4 = \breve{\gamma}_3\theta$.[11] The inclusion of skill shares in the production function specification as in (10) in order to control for heterogeneity of labour quality is a common approach in the literature (see, for example, Lehr and Lichtenberg, 1999, Caroli and van Reenen, 1999, Bresnahan *et al.*, 2002, and Hempell, 2005). I use OLS for the estimation of this block of the model.

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[9] Note that I do not impose constant return to scale, whereas ICT is allowed to affect productivity both directly (through the ICT capital variable) and indirectly (through the innovation output variable). The latter extension of the standard CDM model requires the use of exclusion restriction(s) or the non-linear functional form for identification of the total effect of ICT on productivity. I do use the non-linear functional form for identification of the model and I have some variables that are included in the vector of firm characteristics x_{it}^{inno} in the innovation equation and not in the vector x_{it}^{p} in the productivity equation. However, as I will discuss in more detail in Section 4, I cannot really claim to find causal effects of R&D and ICT on innovation and productivity. Therefore, all reported results in the paper should be viewed as representing associations rather than causal relationships.

[10] This number of years of education corresponds to completed upper secondary education or vocational training.

[11] The first–order Taylor approximation is quite accurate if the values of θ and h are not too large. Anticipating some of the results and applying mean shares for h, the implicit product θh=0.05 is small enough for the approximation to work well (for values <0.1 the absolute error of the approximation is less than 0.005).

3. Variables construction and descriptive statistics

3.1 Data sources and variables

For the analysis, I use a rich firm-level panel data set based on the four recent waves of the *Community Innovation Survey* for Norway: CIS2004 (period: 2002–2004; *N* = 4655), CIS2006 (period: 2004–2006; *N* = 6443), CIS2008 (period: 2006–2008; *N* = 6012) and CIS2010 (period: 2008–2010; *N* = 6595). These data are collected by Statistics Norway as a part of the annual R&D survey (I refer 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 prior to each survey. The firms included in the surveys are a large and representative sample of the Norwegian private sector. The firms with 10–50 employees are selected using a stratified sampling method based on industry classification (NACE codes) and firm size, whereas all firms with more than 50 employees are included. These data are then supplemented with information on the number of patent applications from the Norwegian patent database and ICT investments from Investment statistics for the years 2002–2010. Finally, by supplementing these data with information about firms and employees from different registers and excluding firms with incomplete information or with extreme observations for the key variables, I obtain an unbalanced panel of 14 533 observations on 8 554 firms.[12] Table 1 presents an overview of the main variables and the data sources applied in the study. A more detailed description of the data sources and distribution of the final sample across industries are provided 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 Oslo Manual (OECD, 2005). For definitions and examples of different types of innovations, see Appendix B. In the Innovation survey, firms are asked to state whether they have introduced a given type of innovation

[12] In addition to requiring non-missing data for each variable except R&D intensity (since I use the predicted values for that variable) and firm age (a dummy for missing observations is used as one of the age dummies), I exclude the observations from the first and last percentiles of distributions for the following key variables: log R&D intensity, log ICT investment intensity, log ICT capital intensity, log tangible capital intensity and log value added per employee. The former has resulted in a reduction of the initial sample of 23 705 observations by about 31 per cent (N=2240 for missing observations on ICT investment and N=5147 for missing observations on other variables), while the latter reduced the initial sample by 5.7 per cent (N=1355). I also exclude the observations (N=430) for the firms in the 'Hotels and restaurants' industry (NACE 55), since they are only included in the CIS2010 data. Since I get few observational units with more than one year per firm (about 6o per cent of firms are only represented once in the sample and the average number of observations per firm is 1.6), I treat the final sample as cross-section data. However, in order to account for firm heterogeneity, I pool all available observations and adjust the standard errors for clustering at the firm level when estimating the model.

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.* 1998, where they include such a variable). This is, probably, due to a lack of such information at the firm level. In this paper, I take 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 simply the total number of patents applied for by the firm through the Norwegian Patent Office over the three years in the given sub-period. While the introduced innovation types show the *variety* of innovative process in the firm, the number of patent applications reflects the *quality* of the innovation, i.e. only the best innovative products are expected to be protected by patents.[13]

Table 1. Overview of 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]	R&D statistics
sumpat	Number of patent applications[a]	Patent database
R	R&D investment[b]	R&D statistics
L	Number of employees	R&D statistics
ICT	ICT investment[b]	Investment statistics
ICTK	ICT capital services[b,c]	Investment statistics
K	Tangible 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	Tangible capital intensity: *K/L* (log)	
l	Number of employees (log)	
lp	Labour productivity: *Y/L* (log)	

[a] Measured over the three-year period preceding the year of the survey.
[b] The units of measurement are NOK thousands in real terms (base year = 2001).
[c] The variable is measured at the beginning of the year.
[d] Man-hours according to labour contracts.

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 calculated in

[13] For example, only 17 per cent of innovative firms in CIS2004 applied for a patent during 2002–2004.

2001 prices).[14] R&D intensity, r, is the R&D investment per employee, R/L, where L is the number of employees.

Since 2002, Statistics Norway has collected micro-level information on investment expenditures on ICT, i.e. on purchased hardware and purchased and/or own-account software. ICT investment, *ICT*, is the total annual ICT expenditures. As deflators to obtain real expenditures I use the National Account price indices of the corresponding investment types. Then, by analogy to R&D intensity, r, ICT intensity, *ict*, is calculated as ICT investment per employee. These two variables are used as the main explanatory variables in the innovation output equation.

The ideal measure capturing the economic contribution of capital inputs in a production theory context is flow of capital services (see Draca *et al.*, 2007). Only in a very few studies the authors construct a measure of ICT capital based on information about investments in hardware and software (see, however, Hempell, 2005, and Farooqui and van Leeuwen, 2008). Using the Perpetual Inventory Method (PIM procedure) applied in these studies and using information on ICT flows over consecutive time periods, I construct a measure of ICT capital services, *ICTK*.[15] Further, the variable K is a measure of tangible capital services, which are calculated based on the book values of a firm's tangible assets (see, Rybalka, 2009, for details of the construction procedure for both capital measures). Then, ICT and tangible capital intensities, *ictk* and k, used in the production function analysis are calculated as the corresponding capital stock per employee at the *beginning* of year t. The 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 the CPI.

Finally, the variable h is defined as the number of man-hours worked by employees with high education (corresponding to completed upper secondary education or vocational training) divided by the total number of man-hours in the firm. I assume 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, I use the following firm-specific characteristics in the analysis:

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[14] More than 60 percent of total R&D expenditures are labour costs.

[15] I use all available data on the firm's ICT investments from annual 2002–2010 Investment statistics for ICT capital construction.

- *Market location*: a set of dummy variables indicating whether a firm sells its *main* products or services in local/regional, national, European 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 preceding the observation year.
- *Cooperation on innovation*: a set of dummy variables indicating whether the firm cooperated with others (another firm or university/college/research institute) in Norway, Scandinavia, the EU or the rest of the world (or cooperation in general), 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 the two-digit NACE level (see Table A1 for the distribution across industries of the final sample).[16] Manufacture of food products and beverages (NACE 15) is the reference industry for manufacturing firms and Wholesale (NACE 51) is the reference industry for firms in services and for the whole sample.
- *Firm location*: a set of dummy variables indicating the region where the firm is located, i.e. North, South, West, East coast, East inland, central Norway, and the capital region (Oslo and Akershus). The latter category is the reference category.
- *Year*: a set of time dummies indicating the year of the Innovation survey; 2004 is the reference year.

[16] At all estimation stages and for all sub-samples, I include 2-digit industry dummies in order to control for industry-specific differences. While differences may also be present within 2-digit industries, further specification is not possible due to the small number of observations in some of the sub-industries.

3.2 Descriptive statistics

Table 2 presents the mean values of the main variables for different data samples (more descriptive statistics for the final sample are reported in Table A2). Column (1) in Table 2 describes the final sample of 14 533 observations of 8 554 firms. In this sample, almost half of the observations (approximately 48 per cent) concern firms that engage in some sort of innovation activity, while only 30 per cent report positive R&D investment, with an average of NOK 108 000 per employee. This fact confirms that many firms may have some kind of innovative effort without reporting R&D (see Griffith *et al.*, 2006). While nearly 90 per cent of the firms in the sample invest in ICT, the intensity with which they invest is much lower compared to R&D investment intensity, i.e. less than NOK 24 000 per employee. Roughly 30 per cent of the employees are high-skilled workers on average.

Table 2. Mean values of key variables for different samples (pooled CIS2004, CIS2006, CIS2008 and CIS2010)

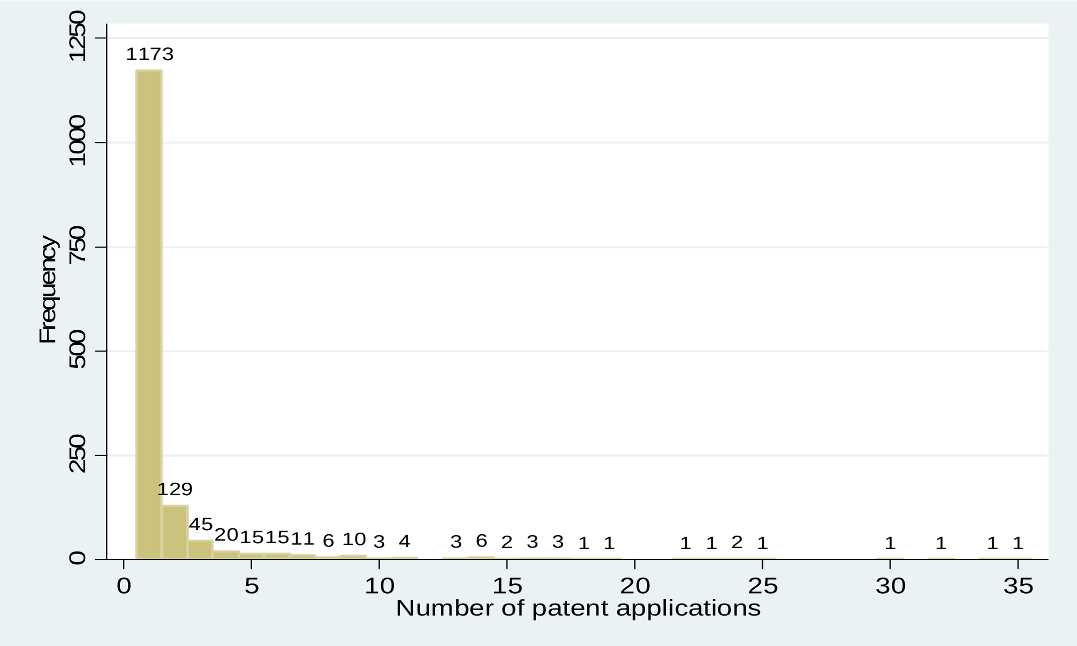
Sample:	(1) Full sample (N=14533)	(2) Obs. on innovative firms (N=6967)	(3) Obs. on non-innovative firms (N=7566)	(4) Obs. on manufacturing firms (N=6199)	(5) Obs. on firms in services (N=6145)
Value added (VA) per employee[a,b]	610.0	640.0	582.4	561.4	685.3
Number of employees[b]	92.6	121.0	66.5	91.3	93.0
Firm age[b]	17.5	17.5	17.5	19.5	16.2
ICT capital services per VA[b]	0.034	0.040	0.029	0.021	0.053
Tangible capital services per VA[b]	0.060	0.062	0.059	0.074	0.049
Share of high-skilled[b]	29.0%	35.0%	23.4%	19.7%	43.8%
Part of a group[c]	61.7%	66.5%	57.3%	63.6%	62.0%
Market location: local/regional[c]	51.6%	38.7%	63.5%	42.6%	49.7%
Market location: national[c]	33.1%	39.6%	27.1%	36.5%	36.7%
Market location: European[c]	9.1%	12.7%	5.7%	12.7%	7.5%
Market location: world[c]	6.2%	9.0%	3.7%	8.2%	6.1%
Recipients of subsidies[c]	15.9%	30.3%	2.7%	21.3%	15.0%
Cooperation on innovation[c]	17.0%	32.0%	3.1%	22.4%	15.5%
Purchased R&D[c]	13.3%	25.1%	2.5%	19.6%	9.9%
R&D investors ($R>0$)[c]	30.1%	55.2%	7.0%	38.9%	29.0%
ICT investors ($ICT>0$)[c]	89.3%	92.8%	86.1%	88.9%	90.3%
R&D investment intensity[a,b,d]	108.0	112.7	73.6	68.2	165.8
ICT investment intensity[a,b,d]	23.6	26.7	20.5	14.8	36.3
Firms with at least one innovation[c]	47.9%	100%	-	55.0%	48.8%
Firms with product innovation[c]	28.8%	60.1%	-	35.8%	29.7%
Firms with process innovation[c]	21.5%	44.8%	-	25.6%	21.6%
Firms with organisational innovation[c]	21.6%	45.1%	-	23.7%	21.6%
Firms with marketing innovation[c]	25.8%	53.8%	-	29.8%	27.3%
Firms with at least one patent[c]	10.1%	18.4%	2.4%	14.5%	8.2%
Number of patent applications[b,e]	2.1	2.2	1.2	2.3	1.8

[a] Units are NOK thousands in real terms (base year = 2001) per employee.
[b] Mean values.
[c] Share of observations with corresponding firm characteristic.
[d] Calculated for the sample of firms with positive investment.
[e] Calculated for the sample of firms with at least one patent application.

Relatively few Norwegian firms have an international orientation, i.e. only 15 per cent of the firms sell their main products or services on the international market (Europe and rest of the world), while more than half of the firms (about 52 per cent) sell their main products or services on the local or regional market, and about 33 per cent operate at the national level. More than 60 per cent of the observations concern firms that belong to a group. The same high shares are observed by Castellacci (2011) for Norwegian CIS data and by Polder *et al.* (2009) for Dutch CIS data (compared to just 25 per cent of Italian manufacturing firms in Hall *et al.*, 2013). That could be the result of the over-representation of medium-sized and large firms in Norwegian CIS data (these firms are often part of a group), i.e. firm size distribution is skewed to the right, with an average of 92, but with a median of only 30 employees (see Table A2). Approximately 17 per cent have cooperated on innovation, either with a university/college/research institute or with another firm, while approximately 13 per cent of the firms purchased R&D services from an external provider. Only 16 per cent of firms in my final sample are R&D subsidy recipients, in contrast to Hall *et al.* (2013), where 42 per cent of the firms receive subsidies (however, their subsidy variable comprises subsidies both for R&D and for other types of investments).

Turning to the innovation output variables, all four types of innovation are well-represented in the data, the shares of observations varying between 21 and 29 per cent (see column 1 in Table 2). As for the combinations of different types of innovation, product innovation only (combination [1,0,0,0]), followed by all types of innovation (combination [1,1,1,1]), marketing innovation only (combination [0,0,0,1]) and organisational innovation only (combination [0,0,1,0]) are the most common innovation combinations among the innovative firms (see the observed frequencies for 16 combinations of four innovation types in Table C5). Not surprisingly, the distribution of the number of patent applications is extremely skewed to the right, with 90 per cent of observations being equal to zero and 80 per cent of those that applied for a patent being equal to one patent application (see Figure 5). Such a distribution of the number of patent applications can be captured by the zero-inflated count data models (see, e.g., Chapter 18 in Greene, 2011). This class of models takes into account that zero counts can arise from one of two regimes, i.e. in one regime, the outcome is always zero (in my case, if a firm does not innovate), and, in the other, the usual count data generating process applies (some innovative firms apply for a patent and some do not).

Figure 5. Distribution of number of patent applications (with N=13066 for zero patent applications and N=8 for more than 35 patent applications)



Columns (2) and (3) in Table 2 present a comparison of the main firm-specific characteristics of innovative and non-innovative firms (the former are defined as those that have introduced at least one type of innovation in the survey period). The comparison shows a remarkable difference between the two groups, which is in line with the previous CDM analyses based on firm-level data for other countries (see, for example, Crepon *et al.*, 1998; and Hall and Mairesse, 2006). On average, innovative firms are much bigger in size, have a higher share of high-skilled employees, an international orientation and a higher probability of belonging to a group than non-innovative firms. They are also more capital intensive. However, the former group is only slightly more productive. About 55 per cent of innovative firms and only 7 per cent of non-innovative firms are R&D performing firms, which supports the fact that R&D is an important input for innovation output. While approximately 18 per cent of innovative firms have applied for at least one patent, 2 per cent of non-innovative firms also have at least one patent application in the patent database. The latter observation is possible if some of the non-innovative firms have applied for a patent for an innovation introduced during the previous three-year period.[17]

[17] These numbers support my intuitive choice of a binary indicator for any type of innovation as a main *inflate* variable when estimating the probability of outcome (the number of patent applications) to be zero or nonzero, i.e. the innovators have much higher probability to apply for a patent than non-innovators.

Finally, columns (4) and (5) in Table 2 present a comparison of the main firm-specific characteristics of manufacturing firms (NACE 15-36 in SN2002) and firms in service industries (NACE 51-74 in SN2002). We can observe a remarkable difference between these two groups. Being on average almost of the same size and slightly younger, firms in service industries are more productive, have a higher share of high-skilled man-hours and are much more ICT capital-intensive (although much less tangible capital intensive). Given that Business-related services (NACE 72-74) and Wholesale (NACE 51) were the most ICT capital-intensive industries in Norway in 2002–2006 (see Table 3 in Rybalka, 2009) and that these industries account for about 75 per cent of observations for the firms in service industries in the final sample (see Table A1), the latter observation is not surprising. At the same time, the firms in the service industries represented are less likely to have their main market abroad, and they also cooperate less on innovative activities, purchase R&D from external providers less often, and receive R&D funding less often. Not surprisingly, their innovative output is lower on average, both when proxied by different innovation types and by the number of patent applications. Interestingly, while there are fewer R&D investors among firms in service industries, those that do invest in R&D invest on average more intensively than R&D investors in manufacturing. One can also observe that the rate of ICT diffusion is high in both sectors (the shares of ICT investing firms are 88.9 and 90.3 per cent, respectively). However, firms in service industries invest more intensively in ICT. Thus, compared to manufacturing firms, firms in service industries appear to be younger, more domestically oriented, and rely relatively more on ICT and skilled labour. Although less innovative, they are, however, more productive.

4. Econometric model specification and estimation issues

This section presents the econometric model specification for the extended version of the CDM model presented in Section 2.

Econometric specification of block 1: R&D input decision

This block is the same for all model specifications. It models an R&D input decision by firm *i* in time *t* and contains two R&D equations corresponding to the theoretical model (1)–(4):

(1´) $$rd_{it}^{*} = x_{it}^{rd}\alpha_1 + e_{it} ,$$

(2´) $$r_{it}^{*} = x_{it}^{r}\alpha_2 + \varepsilon_{it} .$$

Econometric specification of block 2: Innovation output

I use two proxies for innovation output when estimating the second model block based on equation (5), i.e. the probability of innovating and the number of patent applications. The probability of innovating can be estimated for any innovation (basic model) and for each of four different types of innovation (product, process, organisational and marketing innovation). The innovation equation when innovation output is proxied by *any type* of innovation is:

$$inno_{it}^{*} = \delta_1^0 \cdot r_{it}^{*} + \delta_2^0 \cdot ict_{it} + \delta_3^0 \cdot h_{it} + x_{it}^{inno}\beta^0 + \eta_{it}^0 . \tag{3a´}$$

The system of equations for the probability of the *different types* of innovation is:

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

I model the probability of applying for a patent as a function of the binary indicator for any type of innovation, as well as firm age, industry and location, and time dummies. The patent equation is then specified as an expected number of patent counts for the firms that have positive probability of applying for a patent, $sumpat_{it}^{*}$, conditional on R&D intensity, *r*, ICT intensity, *ict*, and other variables equal to:

$$E(sumpat_{it} \mid r_{it}^{*}, ict_{it}, h_{it}, x_{it}^{inno}) = \exp(\delta_1^5 \cdot r_{it}^{*} + \delta_2^5 \cdot ict_{it} + \delta_3^5 \cdot h_{it} + x_{it}^{inno}\beta^5) . \tag{3c´}$$

Econometric specification of block 3: Productivity

The econometric specification of the productivity equation based on the theoretical model (6)–(10) is:

$$lp_{it} = \pi_0 + \gamma_1 k_{it} + \gamma_2 ictk_{it} + \breve{\gamma}_3 L_{it} + \gamma_4 h_{it} + INNO_{it}^{*}\pi_1 + x_{it}^{p}\pi_2 + \zeta_{it} , \tag{4´}$$

where $INNO^*$ is either the predicted probability of any innovation, or the set of dummies for the different combinations of innovation types: [1,1,1,1], [1,1,1,0], [1,1,0,1] etc. (with combination [0,0,0,0] as the reference category), or the expected number of patent applications per employee.[18]

[18] Note that, to simplify the interpretation of the results, I use the predicted values for the number of patent applications divided by the number of employees in the firm as an explanatory variable in the productivity equation (such as *k* and *ictk*, which are the conventional and ICT capital per employee).

This empirical model is a recursive nonlinear system of equations, each of which focuses on one of the steps in the innovation process. The first equation models the probability that a firm with characteristics x_{it}^{rd} engages in R&D activities. It is estimated for the whole sample of firms. The second equation focuses only on firms with positive R&D investment, *R >0*, and studies how the R&D intensity of the firm, r_{it}^{*}, is affected by a set of firm characteristics x_{it}^{r}. The third equation analyses the link between two main innovation inputs (R&D and ICT), on the one hand, and innovation output (either any innovation, four different types of innovation, or the number of patent applications), on the other.[19] Finally, the fourth equation estimates the effects of innovation output together with ICT capital on the labour productivity of the firm (lp_{it}). When estimating the second and third model blocks, I also explore the influence of skill composition on the firm (h_{it}), together with firm characteristics x_{it}^{inno} and x_{it}^{p}, correspondingly. Table 3 describes different firm characteristics that are comprised by the vectors $x_{it}^{rd}, x_{it}^{r}, x_{it}^{inno}$ and x_{it}^{p} (marked by *x*) and other explanatory variables used in the estimation of equations (1´)–(4´).

The choice of explanatory variables, such as *Market location*, *Part of a group*, *Received subsidy* and *Cooperation on innovation* is inspired by both Hall *et al.* (2013) and Polder *et al.* (2009). However, I also include the *Cooperation on innovation* (at the national, Scandinavian, European or world level) and *Purchased R&D* variables in the Innovation output equation. This choice is based on the results in Cappelen *et al.* (2012), who show that firms collaborating with others on their R&D efforts are more likely to be successful in their innovation activities and patenting.[20] Following Castellacci (2011), who estimates the CDM model based on Norwegian data, I also include *Hampering factors* (high costs, lack of qualified personnel and lack of information) in the estimation of the R&D choice model block 1. As Castellacci (2011) demonstrates, these factors are highly relevant for shaping the innovative process and are also valid instruments for handling the endogeneity problem of the R&D intensity variable when using it in the innovation output equation. While Hall *et al.* (2013) only control for the skill composition of the firm in the innovation output equation, I follow the standard CDM model in Crepon *et al*. (1998) and control for the skill composition of the workforce (share of high-skilled man-

[19] The innovation equation (3a´) is estimated as a probit model. Equation (3b´) is a system of four equations with binary indicators of corresponding types of innovations. It is estimated as a quadrivariate probit model using the GHK (Geweke-Hajivassiliou-Keane) simulation algorithm (see Chapter 15 in Greene, 2011; and Cappellari and Jenkins, 2003), assuming the mutual dependence of the error terms. Finally, equation (3c´) is estimated as a zero-inflated negative binomial count data model by pseudo maximum likelihood.

[20] At the same time, Cappelen *et al*. (2012) demonstrate that getting an R&D tax credit has a marginal effect on innovation (they only find a positive and significant effect for process innovation) and no effect on patenting. Hence, I choose not to control for receiving an R&D subsidy in the innovation output equation (in line with Hall *et al.*, 2013, and Polder *et al.*, 2009).

hours) also in the productivity equation. Further, I provide robustness checks for inclusion of that variable in the innovation output and productivity equations.

Table 3. Variables and methods used in the estimation of different model equations

	Eq. (1´)	Eq. (2´)	Eq. (3´)	Eq. (4´)
Dependent variable:	Dummy for R>0	log(R&D spending per employee)	Any innovation/ four types of innovation / number of patent appl.	log(VA per employee)
Explanatory variables:				
Employment (log)	*x*	*x*	*x*	*x*
Employment squared (log)	*x*	*x*	*x*	*x*
Positive R&D history[a]	*x*			
Market location[b]	*x*	*x*		
Part of a group[b]	*x*	*x*		
Hampering factors[b]	*x*	*x*		
Received subsidy[b]		*x*		
Cooperation on innovation[c]		*x*	*x*	
Purchased R&D[c]			*x*	
R&D intensity (log)[d]			r^*	
Share of high-skilled			*h*	*h*
ICT intensity (log)[e]			*ict*	*ictk*
Tangible capital intensity (log)[e]				*k*
Innovation output[d]				$INNO^*$
Age dummies	*x*	*x*	*x*	*x*
Industry dummies	*x*	*x*	*x*	*x*
Regional dummies	*x*	*x*	*x*	*x*
Time dummies	yes	yes	yes	yes
Estimation method:	Maximum likelihood (ML) by Heckman procedure		ML for probit / GKH simulation for quadrivariate probit / pseudo ML for zero-inflated count data	OLS

Notes: Different firm characteristics that are comprised by the vectors $x_{it}^{rd}, x_{it}^{r}, x_{it}^{inno}$ and x_{it}^{p} are marked by *x*.
[a] Exclusion restriction when estimating (1´) and (2´) by Heckman procedure.
[b] Used to instrument the R&D intensity variable, r^*, when estimating (2´) and using predictions for r^* in (3´).
[c] Used to instrument the innovation output variable, $INNO^*$, when estimating (3´) and using predictions for $INNO^*$ in (4´).
[d] Predicted from the previous estimation stage.
[e] Set to zero when the corresponding investment is zero and dummies for such observations are included.

Identification

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 firms 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 (see Griffith *et al.*, 2006) and some firms may underestimate their R&D (e.g. when it is performed by workers in an informal way).[21] In line with the previous CDM empirical studies, I correct for the selection bias by estimating (1´) and (2´) as a system of equations by maximum likelihood, assuming that the error terms in (1´) and (2´) are bivariate normal with zero mean and covariance matrix as specified in equation (4). In the literature, this model is often referred to as a Heckman selection model (see Heckman, 1979) or type II Tobit model (see Amemiya, 1984). For identification of such a model, the vector x_{it}^{rd} in equation (1´) should contain at least one variable that is *not* in the vector x_{it}^{r} in equation (2´). Nevertheless, all previous works in the CDM literature use the same explanatory variables in both equations. The main reason for this practice is that it is difficult to find the factors explaining a firm's likelihood of engaging in R&D that are not related to the amount of resources the firm decides to invest in R&D. In addition to identification 'by functional form', I use a dummy variable for the firm's previous R&D investments (whether a firm had any R&D activity in the previous 3 years) as an exclusion restriction. On the one hand, I believe that firms that have previous R&D experience have a higher probability of engaging in R&D activities in the given period. On the other hand, it is not obvious that having R&D experience implies higher R&D intensity in the given period (it can happen that 'new' R&D investors, or firms that took a break from investing in R&D, invest more intensively in R&D in the given period than firms that invest continuously).[22] I elaborate more on the selectivity issues 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 Section 5 when estimating the model.

The second econometric issue refers to the endogeneity of some of the main explanatory variables. Since (1´)–(4´) is a system of recursive equations, it is natural to assume that the main explanatory variable in Equation (4´) (innovation output) is endogenously determined in the previous innovation stage, i.e. in innovation equation (3´); in turn, the main explanatory variable in Equation (3´) (innovation input) is determined in the previous innovation stage, i.e. the R&D intensity equation (2´). The standard CDM model handles this problem of the R&D intensity endogeneity by predicting R&D intensity, r_{it}^{*}, from the estimates of the first block of the model (R&D input decision) and using it as an explanatory variable in the innovation equation (3´). Similarly, to handle the endogeneity of the

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[21] Asheim (2012) points to underreporting of R&D investments and innovation activities in the national R&D statistics as one of the possible explanations for the Norwegian productivity puzzle.

[22] The correlation between the *Positive R&D history* variable and the dummy for positive R&D in the given year is 0.65, while the correlation with the R&D intensity variable (r_{it}^{*}) is only -0.01. Note that this variable is equal to zero, both in the case of no R&D activity in the previous 3 years and in the case of missing information on R&D activity in the previous 3 years (about 30 per cent of observations in the final sample). To control for the latter case, I add the dummy variable *No information on R&D history* when estimating (1´).

innovation output variable in (4´), the CDM model uses predicted values of innovation output $INNO_{it}^{*}$ from the estimates of the second block of the model as an explanatory variable in the productivity equation (4´).[23] Note that the variables *Market location*, *Part of a group*, *Hampering factors* and *Received subsidy* do not enter directly in the innovation equation (see Table 3), but only indirectly through research. Hence, these variables can be used as instruments for the prediction of r_{it}^{*} (this choice is inspired by Hall *et al.*, 2013, Polder *et al.*, 2009, and Castellacci, 2011). Further, the variables *Cooperation on innovation* and *Purchased R&D*, which are important for innovation output (see Cappelen *et al.*, 2012), are explicitly assumed to only influence productivity indirectly through innovation and are used as instruments for the prediction of innovation output $INNO_{it}^{*}$. These assumptions impose some a priori structure on the model, which is inspired by the previous CDM studies and which helps identification of the model.

One should also keep in mind the possible endogeneity of other explanatory variables, i.e., the *ict* variable in (3´) and the *ictk* and *k* variables in (4´). With respect to the ICT intensity variable, *ict*, in (3´), I follow Hall *et al.* (2013) and use the reported values of ICT investments in year *t* and treat them as exogenous to innovation output. However, I check the robustness of the results by including the lagged ICT capital intensity as an alternative ICT variable in (3´), $ictk_{t-2,}$ (the ICT capital intensity at the start of the corresponding survey period) and also by instrumenting and including the predicted values of the ICT intensity variable, as Polder *et al.* (2009) do. As regards the capital variables *ictk* and *k* in (4´), they are by construction calculated at the beginning of year *t* and, hence, can be treated as predetermined inputs relative to productivity in the year *t*.

Next, since I have a panel data set (pooled data from the four waves of the innovation survey: CIS2004, CIS2006, CIS2008 and CIS2010), it is important to think about an appropriate panel estimation strategy. However, there are few firms with more than one firm-year observation (about 60 per cent of firms are represented only once in the sample, with the average number of observations per firm being 1.6). I therefore pool all firm-year observations and, for each of the four equations, adjust the standard errors for clustering at the firm level.

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[23] In case of four different innovation types, I generate the predicted probabilities of the $2^4 = 16$ possible combinations of these four types of innovation (all of which exist in my data) and use them as input variables in (4´). The predictions QP1111=Pr*(*pdt*=1,*pcs*=1,*org*=1,*mkt*=1), QP1110= Pr*(*pdt*=1,*pcs*=1,*org*=1,*mkt*=0), etc., correspond to the propensities for the respective combinations [1,1,1,1], [1,1,1,0] etc. Since these add up to one, it is necessary to use one combination as a reference category to avoid perfect collinearity. I use [0,0,0,0] as the reference category.

Finally, the timing of the questions in the survey is such that one cannot really claim a direct causal relationship between R&D and ICT investment, on the one hand, and innovation, on the other, 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. The reported results should therefore be viewed as representing associations rather than causal relationships.

5. Empirical results

This section presents the estimation results of the augmented CDM model. The first model block (R&D input decision) is estimated using the whole sample. Since we can expect the importance of R&D and ICT to differ between industries, the second (Innovation output) and third (Productivity) model blocks are estimated both for the whole sample and separately for manufacturing and services.

5.1 Estimation results of model block 1: R&D input decision

I first test for selection in R&D reporting and use the same test as in Hall *et al.* (2013), where one first estimates 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>0 and the corresponding Mills' ratio. Then I estimate 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 as regressors. The presence of selectivity bias is then tested for by looking at the significance of these 'control functions'.[24] The results of this test are reported as model (1) in Table 4. The predicted probability terms are jointly significant, with a $\chi^2(5)$ = 11.41. I therefore conclude that selection bias is present in my data on R&D and estimate the first model block as a system of two equations by maximum likelihood.

The results of model (2) in Table 4 support the presence of selection with a highly significantly estimated correlation coefficient ρ of almost -0.24. As expected, the *R&D investment history* variable has a positive impact on the propensity to invest in R&D, indicating the extent of *persistency* in the firms' R&D policy. This variable seems to be correlated with the firm size variable, which is not significant when the *R&D investment history* is controlled for (see coefficients for *Employment* in

[24] This procedure is a generalisation of Heckman's two-step procedure for estimation when the error terms in the two equations are jointly normally distributed. The test here is a semi-parametric extension for non-normal distributions.

model (2) and models (3) and (4) in Table 4 for comparison).[25] This is probably due to the fact that larger firms invest more often in R&D than smaller firms. The exclusion of the *Positive R&D history* variable in the selection equation changes the sign of the estimated correlation coefficient ρ between the regression error and selection error terms, resulting in the opposite direction of selection bias (comparing models (2) and (3) in Table 4). If, in addition, I use the same explanatory variables in both the selection and R&D intensity equations (as in Hall *et al.*, 2013), the Heckman procedure fails to identify the selection bias in my data (see the results fo model (4) in Table 4).[26] This is possibly because the *Received subsidies* variable used here can differ from the similar one used in Hall *et al.* (2013), i.e. their variable covers subsidies for investments in general, while my variable only covers subsidies for R&D. As a result, receiving a subsidy automatically implies R>0 and, hence, leads to the extremely high estimated coefficient for the *Received subsidies* variable in the selection equation of model (4) in Table 4 and to the collinearity problems in the R&D intensity equation (see Stolzenberg and Relles, 1997).[27] Stolzenberg and Relles (1997) also noted that a downward-biased estimate could be quite useful for testing a substantive hypothesis of a positive impact of the variable of interest (then we might reasonably conclude that a lower-bound estimate of the corresponding coefficient has been found). Keeping that in mind, I use model (2) in Table 4 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 (2) in Table 4) are in line with the previous results in the CDM model literature. A firm's international orientation (reflected by main product market location variables) is 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 (Aw *et al.*, 2007). 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.

[25] Models (2)-(4) differ only by the set of explanatory variables in the selection equation for R&D, with model (3) and model (4) being similar to those in Polder *et al.*, 2009, and Hall *et al.*, 2013, correspondingly.

[26] The further use of the predictions for the R&D intensity from this model specification also resulted in lack of convergence of the likelihood function for the zero-inflated model when analysing the data on patent applications.

[27] By simulations, Stolzenberg and Relles (1997) demonstrate that the well-known two-step Heckman estimation procedure is not a universal procedure against the selection bias problem, since it can both increase and decrease the accuracy of regression coefficient estimates. So, the choice of the explanatory variables for the estimation of sample selection model seems to be important.

Table 4. Estimation results - Sample selection model for R&D choice

	(1)		(2)		(3)		(4)	
	Probit	OLS	Sample	selection	Sample	selection	Sample	selection
Dependent variables:	Prob. of R>0	log(R&D per empl.)	Prob. of R>0	log(R&D per empl.)	Prob. of R>0	log(R&D per empl.)	Prob. of R>0	log(R&D per empl.)
Employment (log)	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]
Employment squared (log)	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: European	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]
<u>Exclusion restriction:</u>								
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 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Models (2)-(4) differ by the sets of explanatory variables in the selection equation for R&D and are estimated by maximum likelihood using the Heckman procedure in Stata.
*** p<0.01, ** p<0.05, * p<0.1

For comparison with the R&D equation, I also estimate the corresponding models (with and without controlling for selection) for ICT investment (see models (3) and (4) in Table C1). The specification is the same as for R&D investment with one exception: I use a dummy for positive ICT capital lagged two years, $ictk_{t-2}$, 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 because it is less subject to market failure than R&D. ICT is also less plagued by uncertainty and more easily tracked.[28] Hence, models (3) and (4) yield identical results for ICT intensity. Like R&D, ICT intensity

[28] Roughly 90 per cent of observations on ICT investment are positive, compared to 30 per cent of positive observations on R&D.

increases with the firm's international orientation (communication possibilities become more important when a firm is engaged in activities abroad), but its impact on ICT intensity is lower. Group membership (better internal access to sources of financing), cooperation on innovation and the magnitude of the hampering factor 'lack of qualified staff' (in both cases, communication possibilities are vital) also have a positive impact on ICT intensity. Interestingly, receiving subsidies (which are R&D investment subsidies) increases ICT investment by 14 per cent on average, probably due to the fact that more financial resources become available for other types of investment when a firm receives a subsidy for carrying out 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 by Hall *et al.*, 2013). Both R&D and ICT intensities vary with firm age, industry and location, and with time.

Based on the results in Table C1, which explores the selection issues of R&D and ICT reporting, and following Hall *et al.* (2013), in the next section of the paper, I use the predicted values of R&D intensity (the expectation of R&D intensity conditional on the other firm characteristics) and the reported values for ICT investment intensity to explain the propensity for different types of innovation and number of patent applications. I further explore 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 at the start of the corresponding survey period, or by instrumenting and including the predicted values of the ICT intensity variable (based on model (4) in Table C1), as Polder *et al.* (2009) do.

5.2 Estimation results of model block 2: Innovation output

Tables 5–7 report the results of the estimation of innovation output equations (3a´) – (3c´) for different innovation output proxies (any type of innovation, four types of innovation and the number of patent applications) and for three different samples of firms (all firms, firms in manufacturing and firms in service industries).

Measuring innovation output with one dummy for any type of innovation

Table 5 reports the results of the simple probit model estimation of equation (3a´) for any type of innovation and for all three samples of the firms under investigation. I present these results first, mainly to compare them with those obtained by Hall *et al.* (2013), who use the model specification for any type of innovation as their main specification. In addition, I provide different robustness checks for this case. From Table 5, we can see that, irrespective of the sample, the propensity to innovate has a similar relationship to the main explanatory variables, increasing strongly with R&D and ICT intensities, the share of high-skilled workers and firm size. In addition to the positive impact of ICT intensity, not having any ICT investment at all is negative for the propensity to innovate.[29] However, the impact of ICT intensity is substantially lower than the impacts of R&D intensity and share of high-skilled man-hours, indicating that the latter two factors are relatively more important for innovation than ICT (this result is in line with those obtained by Hall *et al.*, 2013). Interestingly, while R&D intensity is of similar importance for innovation in both industries, skills and ICT intensity are relatively more important for innovation in manufacturing. Given much lower levels of ICT intensity in manufacturing (measured both as ICT capital services per value added and as ICT investment per employee, ref. Table 2), the latter finding suggests the conclusion that Norwegian manufacturing firms may be underinvesting in ICT compared to firms in service industries.

Table 5: Estimation results - Innovation output: Any type of innovation (by industry)

Sample:	All firms			Manufacturing			Services		
	Coeff.	S.e.	Btstr.	Coeff.	S.e.	Btstr.	Coeff.	S.e.	Btstr.
Predicted R&D intensity (log)	0.836 ***	0.043	[0.041]	0.803 ***	0.063	[0.056]	0.812 ***	0.062	[0.061]
Share of high-skilled	0.500 ***	0.076	[0.072]	0.780 ***	0.143	[0.129]	0.385 ***	0.096	[0.083]
ICT intensity (log)	0.046 ***	0.010	[0.010]	0.074 ***	0.018	[0.016]	0.026 *	0.015	[0.015]
Zero ICT investment	-0.125 ***	0.044	[0.042]	-0.165 ***	0.066	[0.063]	-0.118 *	0.073	[0.065]
Employment (log)	0.749 ***	0.059	[0.051]	0.812 ***	0.096	[0.084]	0.678 ***	0.086	[0.074]
Employment squared (log)	-0.030 ***	0.007	[0.006]	-0.040 ***	0.012	[0.010]	-0.026 ***	0.010	[0.008]
Cooperation: National	0.564 ***	0.050	[0.043]	0.567 ***	0.071	[0.069]	0.523 ***	0.077	[0.075]
Cooperation: Scandinavia	0.335 ***	0.100	[0.093]	0.448 ***	0.140	[0.124]	0.294 *	0.162	[0.162]
Cooperation: EU	0.026	0.097	[0.118]	0.142	0.150	[0.147]	-0.044	0.143	[0.145]
Cooperation: World	0.198	0.121	[0.130]	0.249	0.221	[0.202]	0.289 *	0.166	[0.176]
Purchased R&D	0.622 ***	0.052	[0.048]	0.663 ***	0.068	[0.066]	0.590 ***	0.088	[0.073]
Number of observations	14533			6199			6145		
Non-zero observations	6967			3412			2997		
Log likelihood	-7804.49			-3234.75			-3459.13		

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, 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 (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level. Bootstrap standard errors [in brackets] are based on 100 replications.
Dependent variable: binary indicator for any type of innovation. Estimated by maximum likelihood as a probit model in Stata.
*** p<0.01, ** p<0.05, * p<0.1

As for other explanatory variables, cooperation on innovation (at the national and Scandinavian level) and the purchasing of R&D from external providers are also strongly associated with innovation, in both manufacturing and service industries. These results suggest that the external acquisition of knowledge from specialised 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

[29] About 10 per cent of observations on ICT investment are zeros. Since the log of the ICT investment intensity is used in the empirical specification (and, as a consequence, firms with zero ICT investment would turn into missing observations), I convert missing log-values to zeros and add a dummy variable for zero ICT investment.

obtained earlier based on Norwegian data by Cappelen *et al.* (2012), who show that firms collaborating with others on their R&D are more likely to be successful in their innovation activities, including patenting.

As mentioned earlier, I use the predicted R&D intensity in the analysis of the innovation equation in the CDM model. Using the predicted values for R&D intensities 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 investment and innovative outcomes. However, given that the model is estimated sequentially, conventional standard error estimates will be biased. Therefore, Table 5 also presents bootstrap standard errors based on 100 replications. In general, we can see that bootstrapping makes relatively little difference to the standard errors and the significance levels. Hall *et al.*, 2013, and Polder *et al.*, 2009, obtain the same results for bootstrapping of standard errors in their analysis.[30]

Robustness checks for inclusion of skill variable in the innovation output equation

I check 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 order to compare my results with those in Polder *et al.*, 2009, who do not use a skill variable and with those in Hall *et al.*, 2013, who check for the importance of an interaction term for their sample of manufacturing firms). The results by industry are presented in Table C2. The impacts of R&D and ICT intensities remain positive and highly significant, irrespective of the inclusion or exclusion of the skill variable. In contrast to Hall *et al.* (2013), the inclusion of an interaction term does not show evidence of complementarity between skills and R&D intensity in manufacturing, while the estimated effect of the interaction term is positive and highly significant in service industries. The estimates of the other coefficients in the basic model are largely unchanged by the addition of these variables.

Exploring the endogeneity of the ICT variable in the innovation output equation

In order to check for possible endogeneity of the ICT intensity variable in the innovation output equation (since I use the observed ICT intensity in period *t*), I first re-estimate equation (3a´) by using the ICT capital intensity lagged two years as an input ICT variable, $ictk_{t-2}$ (the log of ICT capital per employee at the start of the corresponding survey period). Then I re-estimate equation (3a´) by instrumenting and including the predicted values of the ICT intensity variable based on model (4) in

[30] All further results are also robust to bootstrapping of standard errors, but are only reported with conventional standard errors.

Table C1 (as Polder *et al.*, 2009, do). The results are presented in Table C3, where model (1) corresponds to the basic model with the observed ICT intensity, model (2) corresponds to the use of the lagged ICT intensity and model (3) corresponds to the use of the predicted ICT intensity. The use of the lagged ICT capital intensity marginally changes the main results (compare the results for model (1) to those for model (2) in Table C3). Furthermore, using the predicted ICT investment intensity together with the predicted R&D intensity results in a substantial reduction in the impact of the R&D intensity variable and a huge increase in the impact of the ICT intensity variable.[31] I interpret these results as a manifestation of the limitations of instrumenting two somewhat similar variables using the same set of predictors. This can lead to a multicollinearity problem in the innovation output equation. I further conclude that the potential endogeneity problem of the observed ICT intensity variable is not crucial to the results and proceed to analyse other measures of innovation output using my basic specification (with the observed ICT intensity).

Measuring innovation output with dummies for four different innovation types

Table 6 reports the estimation results of the quadrivariate probit model (3b´) when the innovation output is measured with dummies for four different types of innovation (product, process, organisational and marketing innovation). To explore the hypothesis that the importance of innovation modes can differ between industries, Table 6 only focuses on the results for the manufacturing firms and firms in services (the results for the whole sample are presented in Table C4).[32]

Firstly, we can see that the independence of the error terms across equations in (3b´) is rejected, with highly significant values in a χ^2-test for all rho equal to zero ($\chi^2(6)$ =1382.10 and $\chi^2(6)$ =1749.67 for the sample of manufacturing firms and firms in services, respectively).[33] All four innovation types have similar relationships to the main explanatory variables, increasing strongly with the R&D and ICT intensities, the share of high-skilled workers and firm size. More specifically, the results confirm earlier findings that ICT is relatively more important for product innovation in manufacturing and for

[31] In Polder *et al.* (2009), the R&D intensity is even insignificant for the innovation output in most of the cases (one exception is product innovation in manufacturing firms), which appears to be an unusual result in the CDM literature, while the estimated coefficients of the predicted ICT intensity are very high.

[32] The estimation is done in Stata using the program *mvprobit* (see Cappellari and Jenkins, 2003) with the number of draws for the GHK simulator equal to 80 for the sample of manufacturing firms and firms in services, and to 120 for the whole sample. As documented in Cappellari and Jenkins (2003), the number of random draws, which is approximately equal to the square root of the sample size, is sufficiently large to simulate estimates that are similar to the corresponding ML estimates. For the prediction and further use of joint probabilities for four innovation types QP1111=Pr*(*pdt*=1, *pcs*=1, *org*=1, *mkt*=1), QP1110= Pr*(*pdt*=1, *pcs*=1, *org*=1, *mkt*=0) etc., I adopted and re-programmed the estimation routines from the Stata program *mvped* (that only predicts 'all successes', QP1111, and 'all failures', QP0000) in order to get all 16 combinations.

[33] This is the test that all correlations $\rho_{jk} = \rho_{kj}$ between η^k and η^j in (3b´), $j, k = 1, 2, 3, 4$ and $j \neq k$, are jointly equal to zero.

process innovation in service industries (see, for instance, Vincenzo, 2011). Not having any ICT investment at all is strongly negative for process and organisational innovation in manufacturing firms and for product and marketing innovation in firms in the service sector.

Table 6: Estimation results - Innovation output: Four types of innovation (Manufacturing firms versus firms in services)

Innovation type:	New product		New process		Organisational		Marketing	
	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
Manufacturing firms (6199 observations, 3386 firms)								
Predicted R&D intensity (log)	0.800 ***	0.061	0.598 ***	0.059	0.165 ***	0.057	0.360 ***	0.054
Share of high-skilled	0.814 ***	0.150	-0.038	0.154	0.389 ***	0.149	0.453 ***	0.138
ICT intensity (log)	0.089 ***	0.019	0.043 **	0.018	0.048 ***	0.019	0.053 ***	0.018
Zero ICT investment	-0.068	0.074	-0.286 ***	0.075	-0.169 **	0.081	-0.050	0.070
Employment (log)	0.708 ***	0.103	0.419 ***	0.096	0.971 ***	0.090	0.433 ***	0.087
Employment squared (log)	-0.032 **	0.012	-0.013	0.011	-0.073 ***	0.010	-0.028 ***	0.010
Cooperation: National	0.504 ***	0.064	0.484 ***	0.059	0.419 ***	0.059	0.467 ***	0.057
Cooperation: Scandinavia	0.162 *	0.098	0.348 ***	0.080	0.270 ***	0.079	0.245 ***	0.080
Cooperation: EU	0.227 **	0.102	0.024	0.085	0.043	0.083	0.007	0.090
Cooperation: World	-0.184 *	0.109	-0.078	0.103	0.031	0.096	-0.109	0.097
Purchased R&D	0.490 ***	0.058	0.299 ***	0.056	0.206 ***	0.054	0.248 ***	0.055
Non-zero observations	2217		1590		1467		1848	
Chi-square for all rho=0	1382.10 ***							
Log likelihood	-11292.29							
Firms in services (6145 observations, 3947 firms)								
Predicted R&D intensity (log)	0.953 ***	0.063	0.457 ***	0.060	0.316 ***	0.058	0.378 ***	0.058
Share of high-skilled	0.592 ***	0.104	0.083	0.102	0.221 **	0.108	0.169 *	0.097
ICT intensity (log)	0.035 **	0.017	0.042 **	0.016	0.037 **	0.016	-0.001	0.015
Zero ICT investment	-0.153 *	0.091	0.061	0.085	0.043	0.088	-0.190 **	0.077
Employment (log)	0.493 ***	0.087	0.247 ***	0.089	1.295 ***	0.098	0.274 ***	0.079
Employment squared (log)	-0.007	0.010	0.002	0.010	-0.100 ***	0.011	-0.009	0.009
Cooperation: National	0.451 ***	0.071	0.430 ***	0.068	0.275 ***	0.066	0.413 ***	0.066
Cooperation: Scandinavia	0.186	0.116	0.203 *	0.112	0.189 *	0.098	0.208 **	0.102
Cooperation: EU	0.066	0.110	-0.148	0.107	0.095	0.102	0.095	0.098
Cooperation: World	0.108	0.139	0.194 *	0.117	0.064	0.100	0.172 *	0.102
Purchased R&D	0.535 ***	0.072	0.370 ***	0.067	0.244 ***	0.066	0.175 ***	0.067
Non-zero observations	1827		1327		1330		1677	
Chi-square for all rho=0	1749.67 ***							
Log likelihood	-10356.82							

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, 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 (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level.
Dependent variables: binary indicators for different types of innovation. Estimated as a quadrivariate probit model by using the program *mvprobit* in Stata (see Cappellari and Jenkins, 2003) with the number of draws for the GHK simulator equal to 80.
*** p<0.01, ** p<0.05, * p<0.1

As regards other explanatory variables, cooperation with others at the national and Scandinavian level (for all types of innovation in both industries), at the European level (for product innovation in manufacturing) and at the world level (for process and marketing innovation in services), together with purchasing R&D services from external providers, are positively related to the propensity to innovate. While cooperation on innovation seems to be relatively more important for innovation in manufacturing, purchasing R&D from external providers has a higher impact on most types of innovation in services.

Measuring innovation output by the number of patent applications

Table 7 reports the results by industry for the estimation of equation (3c´), where another proxy of innovation output is used, i.e. the number of patent applications. Since numbers of patent applications are observed as integer numbers with many zero observations, we can model them as zero-inflated count data and use pseudo maximum likelihood for the estimation.[34] In this model, I use 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 we can expect a higher/lower probability of applying for a patent for some age groups, regions and industries. I use 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 (see Table A2). As shown by the results in Table 7, the dispersion parameter alpha is far from zero, so the negative binomial (NB) specification is preferable to the Poisson specification. A Vuong test compares the zero-inflated NB model to a standard NB model. With a highly significant Vuong test value, I reject the 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 the main variables for innovation, i.e. R&D intensity and workers' skills are strongly associated with patenting, in both manufacturing and service industries, with R&D being more important for patenting in service industries and skills being relatively more important for patenting in manufacturing. ICT intensity also has a positive impact on patenting, but, again, this impact is substantially lower than the impacts of R&D intensity and the share of high-skilled man-hours. Interestingly, in contrast to the results for innovations, the estimated coefficient for zero ICT investment is positive and significant. However, when I re-estimate the model for patent applications with ICT capital lagged two years (see column (5) in Table C3), the ICT variables become insignificant, while re-estimation with the predicted values of the ICT intensity (see column (6) in Table C3) 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 strong conclusions cannot be drawn concerning the impact of ICT on patenting, while

[34] My intuition when choosing a zero-inflated count data model instead of a standard count data model for the patent data analysis is based on the existence of two groups, i.e. the 'always zero group' (those who never innovate and, hence, have no reason to apply for a patent) and the 'not always zero group' (those who innovate, but do not always apply for a patent). The estimation is done in Stata using the *zinb* procedure.

the results for other explanatory variables are robust to different model specifications. Cooperation on innovation and the 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 different innovation types, where cooperation at the national and Scandinavian levels was important, cooperation at the European and world levels is more important for patenting.

Table 7: Estimation results – Innovation output: Number of patent applications (by industry)

Sample:	All firms		Manufacturing		Services	
Predicted R&D intensity (log)	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]
ICT intensity (log)	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]
Employment (log)	1.145***	[0.153]	0.663***	[0.238]	1.983***	[0.251]
Employment squared (log)	-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: Scandinavia	0.041	[0.101]	-0.018	[0.120]	0.158	[0.191]
Cooperation: EU	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)	

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Estimated by pseudo maximum likelihood as a zero-inflated negative binomial (NB) count data model.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.3 Estimation results of model block 3: Productivity

In the last part of the analysis, I look at the productivity impacts of innovation activities.

Exploring the importance of innovation, ICT and human capital for productivity

Tables 8–9 show OLS-estimates of equation (4´) by industry, with and without measures of ICT capital intensity and the skill variable (while Hall *et al.*, 2013, control for the ICT intensity in the productivity equation, but not for the skill composition of the firm, Polder *et al.*, 2009, do not include any of these two variables in the last block of the CDM model). Table 8 shows that, when I proxy innovation with the predicted probability of any innovation conditional on R&D, ICT and the other firm characteristics, I find a positive effect of innovation on productivity, i.e. the introduction of any type of innovation increases productivity by approximately 8 per cent independently of the estimation sample (columns (1) in Table 8). Nevertheless, when I include the ICT capital intensity in the productivity equation (columns (2) in Table 8), the predicted probability of innovation activity loses a substantial part of its impact. ICT capital services per employee appear to be a much better predictor of productivity gains than the probability of innovation predicted by ICT and R&D investments. When I also include the skill variable, the ICT capital coefficient decreases slightly, while the innovation coefficient becomes very low (but still significant) for manufacturing firms and even insignificant for the whole sample and firms in service industries (columns (3) in Table 8). The latter result is in line with those in Crepon *et al.* (1998), who also observe a substantial decrease in the estimated elasticity of knowledge capital for manufacturing firms when the skill variable is included in the productivity equation. These results indicate that both ICT and skills are important inputs to a firm's productivity and should not be ignored when analysing the effects of innovations on productivity and economic growth.[35]

Table 8: Estimation results – Productivity: with any type of innovation (by industry)

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Probability of any innovation (predicted)	0.086*** [0.007]	0.052*** [0.007]	0.012* [0.007]	0.081*** [0.007]	0.043*** [0.007]	0.012* [0.007]	0.078*** [0.012]	0.045*** [0.012]	-0.015 [0.012]
ICT capital intensity (log)		0.107*** [0.005]	0.092*** [0.005]		0.117*** [0.006]	0.102*** [0.006]		0.110*** [0.007]	0.096*** [0.007]
Share of high-skilled			0.472*** [0.031]			0.491*** [0.045]			0.520*** [0.035]
Tangible capital intensity (log)	0.097*** [0.004]	0.076*** [0.004]	0.086*** [0.004]	0.095*** [0.005]	0.078*** [0.005]	0.087*** [0.005]	0.097*** [0.005]	0.070*** [0.005]	0.081*** [0.005]
Employment (log)	0.114*** [0.020]	0.102*** [0.019]	0.107*** [0.019]	0.095*** [0.024]	0.081*** [0.023]	0.088*** [0.022]	0.130*** [0.026]	0.116*** [0.025]	0.115*** [0.024]
Employment squared (log)	-0.010*** [0.002]	-0.008*** [0.002]	-0.008*** [0.002]	-0.005* [0.003]	-0.002 [0.003]	-0.003 [0.003]	-0.015*** [0.003]	-0.012*** [0.003]	-0.011*** [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 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
*** p<0.01, ** p<0.05, * p<0.1

Table 9 reports the OLS estimation results for the productivity analysis when the predicted number of patent applications per employee is used as a proxy for innovation. The estimated semi-elasticities of the number of patent applications per employee are high and significant, being about 0.80 for

[35] However, these results can also be a reflection of the high correlation between knowledge capital (predicted by the R&D and ICT intensities, which are highly correlated with the skill variable, as seen from Table A3) and the skill variable. This correlation raises the delicate problem of whether knowledge capital and skills are substitutable or complementary factors. In the former case, lower estimates (when controlling for skill composition) are the appropriate ones, while, if the latter is true, and in the extreme case where knowledge capital and skills are perfect complements, the higher estimates (when not controlling for skill composition) would be the right ones. Earlier robustness checks of the innovation output equation (see Table C2) did not show evidence of complementarity between skills and R&D intensity in manufacturing, while the estimated effect of the interaction term between R&D intensity and the skill variable is positive and highly significant in service industries, implying that the results from columns (3) in Table 8 are more appropriate for manufacturing firms, and from columns (2) in Table 8 (when not controlling for skill composition) for firms in service industries. However, for firms in service industries, this would mean that increases in a firm's research efforts and knowledge capital do not by themselves result in increased productivity, but must be accompanied by related increases in skills.

manufacturing firms, 0.24 for firms in service industries and 0.33 for the whole sample (columns (1) in Table 9).[36] While the inclusion of the ICT variable slightly reduces the impact of the patent variable (columns (2) in Table 9), if the skill variable is included in addition (columns (3) in Table 9), the patent variable loses (almost) all its significance, with the exception of manufacturing firms, where the corresponding semi-elasticity remains positive, significant and relatively high (0.22 compared to 0.09 in Crepon *et al.*, 1998, for French manufacturing firms), indicating that patenting is relatively more important for increasing productivity in manufacturing, while skills are relatively more important for productivity in service industries.

Table 9: Estimation results – Productivity: with the 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]
ICT capital intensity (log)		0.112***	0.093***		0.122***	0.104***		0.113***	0.095***
		[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]
Tangible capital intensity	0.101***	0.077***	0.086***	0.101***	0.081***	0.087***	0.098***	0.070***	0.081***
(log)	[0.004]	[0.004]	[0.004]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Employment (log)	-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]
Employment squared (log)	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 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
*** p<0.01, ** p<0.05, * p<0.1

Exploring the importance of different innovation types for productivity

Table 10 presents the OLS estimation results (by industry) for the 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, based on a quadrivariate probit estimation of (3b´). The results in Table 10 show that product innovation (alone or in combination with marketing innovation) has a positive impact on productivity in manufacturing (while estimated coefficients for both QP1000 and QP1001 are positive and highly significant, the estimated coefficient for QP0111 is negative and highly significant). While process and organisational innovations seem to be important for productivity in service industries (the estimated coefficients for QP0100 and for both QP0010 and

[36] These semi-elasticities mean, for example, that the difference between the last and first decile in the number of patent applications (from 1 to 3) corresponds to 8.7 per cent higher productivity for the patenting manufacturing firms, and to 3.4 per cent higher productivity for patenting firms in service industries (the author's calculations based on distributions for firm size and the number of patent applications for innovative firms).

QP0011 are positive and highly significant, while the estimated coefficient for QP1101 is negative and highly significant).[37] These results are also reflected in the results for the whole sample of firms (where the Construction industry and some other small industries are included). Interestingly, the introduction of all types of innovation together has a positive but relatively low impact on productivity, compared to the introduction of product innovation (alone or in combination with marketing innovation) in manufacturing and process or organisational innovation in services.

Table 10: Estimation results – Productivity: with combinations of four innovation types (by industry)

Sample:	All firms		Manufacturing		Services	
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]
ICT capital intensity (log)	0.090***	[0.005]	0.100***	[0.006]	0.088***	[0.007]
Tangible capital intensity (log)	0.085***	[0.004]	0.086***	[0.005]	0.080***	[0.005]
Share of high-skilled	0.411***	[0.042]	0.355***	[0.065]	0.535***	[0.041]
Employment (log)	0.075**	[0.034]	0.088**	[0.039]	0.034	[0.050]
Employment squared (log)	-0.006*	[0.003]	-0.002	[0.004]	-0.007	[0.005]
R-squared	0.30		0.36		0.25	
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 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level. QP refers to the combinations of the Quadrivariate Probit model for four innovation types: product, process, organisational and marketing innovation, e.g. QP1001 refers to the combination [1,0,0,1], i.e. the firm has introduced both product and marketing innovations, but not the other two types of innovation.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In general, the results in Table 10 do not provide any evidence for the importance of marketing innovation for productivity (with the sole exception of the case when it is combined with product innovation for manufacturing firms). While product innovation contributes to higher productivity in

[37] Interpreting the coefficients as semi-elasticities, an increase of 1 percentage point (+0.01) in the propensity of introducing only a process innovation in a firm in service industries increases productivity by approximately 4.9 per cent, while the same increase in the propensity of introducing only a product innovation in a manufacturing firm, increases productivity by approximately 0.8 per cent. From the means of the predicted propensities in Table C5, we can see that a 0.01 percentage point change is relatively large. However, this interpretation does not take into account the standard deviations of the propensities and, in general, these results should be viewed as representing associations.

manufacturing and process innovation to higher productivity in service industries, organisational innovation seems to be an important supplement to these two types of innovation.

In order to relate my results to the existing literature that studies the importance of organisational innovation with respect to product and process innovation (see Section 2), I also re-estimate the productivity equation (4´) with the predicted propensities for the combinations of only product, process and organisational innovation (based on the estimation results for the first three equations in (3b´) by trivariate probit).[38] The results are presented in Table C6. These results support the importance of product innovation for higher productivity in manufacturing and of process innovation in service industries (see the results for TP100 and TP010 in Table C6). Product innovation contributes positively to higher productivity in service industries only when accompanied by organisational innovation, and a combination of all three types of innovation contributes positively to productivity in both sectors (see the results for TP101 and TP111). However, a combination of product and process innovation without organisational innovation (see the results for TP110) is associated with lower productivity (irrespective of data sample). It can be argued that, initially, this combination has a disruptive effect, but that it may lead to productivity gains in subsequent periods.[39] It can also be an indication of a negative effect of technological innovation that is not adequately supported by a change in the organisation of a firm (this finding is similar to that for service industries in Polder *et al.*, 2009). Hence, the results in Table C6 support the earlier findings on the importance of the organisational innovation for product and process innovation.

Testing for complementarity of R&D and ICT

Finally, Table C7 provides some tests of the complementarity of R&D and ICT with respect to productivity. The channels through which these two kinds of investment exert their effects are not the same. As a consequence, the question of whether R&D and ICT are complements or substitutes is a legitimate one. While the CDM model assumes that R&D influences firm productivity indirectly via an innovation output, in order to test for complementarity of R&D and ICT, I follow Hall *et al.*(2013) and include log R&D investment intensity (actual or predicted) directly in the production function together with log ICT intensity (either actual or predicted log ICT investment intensity or the actual log ICT capital intensity). Then, if the sign and significance of the estimated coefficient for an interaction term between R&D and ICT intensities is positive, the two types of investment are complements in generating higher productivity; if negative, they can be seen as substitutes.

[38] The results for the trivariate probit estimation are not reported here, but they are available from the author upon request.

[39] Testing for a lagged effect of innovation on productivity requires the introduction of dynamics in the model, which is beyond the scope of the current investigation.

When I use the actual levels of investment (column (1) in Table C7), the interaction term is clearly zero, implying no complementarity or substitution. When I include the predicted values of both variables (column (2) in Table C7), their coefficients become large and have the opposite sign, and the coefficient for the interaction term becomes slightly negative. This result, where the ICT variable takes over much of the power of the R&D variable, is similar to the result when I tested for the endogeneity of the ICT variable in the innovation output equation (see Table C2). It can be explained by the limitations of instrumenting two somewhat similar variables using the same set of predictors. At the same time, the results for the preferred model with predicted R&D and actual ICT intensity (both the ICT investment and ICT capital intensities) indicate a weak complementarity between R&D and ICT for the Norwegian firms, i.e. the estimated coefficient for the interaction term is positive and weakly significant. All in all, these results do not provide any strong evidence for the complementarity of productivity impacts of R&D and ICT. Hence, I conclude that R&D and ICT exert their influence on productivity through unrelated channels. This result is in line with that obtained by Hall *et al.* (2013).

6. Conclusions

This paper examines the firm-level relationships between innovation, productivity and two of their major determinants, namely R&D and ICT. Two measures of innovative output are tested, i.e. different types of innovation (product, process, organisational and marketing innovation, or any innovation) and the number of patent applications. For the analysis, I use a rich firm-level data set based on the four recent waves of the *Community Innovation Survey* for Norway (CIS2004–CIS2010) and apply an extended version of the CDM model, which treats ICT as a *pervasive* input rather than as an input in the production function only.

Beyond presenting results for Norway (one of the countries with a high rate of ICT diffusion), this paper contributes to the existing literature in several ways. Firstly, in order to account for industry heterogeneity, I provide separate results for manufacturing firms and firms in services (in addition to analysing the whole economy). Secondly, I include marketing innovation in the analysis in addition to earlier investigated product, process and organisational innovation. All four types of innovation are equally represented in the data, which makes it possible to analyse the whole set of innovation types and enables a more comprehensive understanding of the innovation process in a firm. Thirdly, I use the number of patent applications as an alternative measure for innovation. While the combination of different innovation types shows the *variety* of innovative processes in a firm, the number of patent applications reflects the *quality* of the innovation. And, finally, I control for workforce heterogeneity and check how that influences the results for ICT and R&D.

When analysing innovation output, I find that the ICT investment intensity is strongly associated with all types of innovation. This finding supports the hypothesis that ICT acts as an enabler of innovation. However, its relative importance for innovation is much lower compared to R&D intensity and workers' skills. The result for ICT intensity is robust to different model specifications and is strongest for product innovation in manufacturing and for process innovation in service industries. Not having any ICT investment is strongly negative for process and organisational innovation in manufacturing and for product and marketing innovation in service industries. Interestingly, while R&D intensity is of similar importance for innovation in both industries, skills and ICT intensity are relatively more important for innovation in manufacturing. Given much lower levels of ICT intensity in manufacturing, the latter finding suggests the conclusion that Norwegian manufacturing firms may be underinvesting in ICT compared to firms in service industries. Given that the firm innovates, the ICT investment intensity is also associated with a higher number of patent applications in manufacturing. While R&D is relatively more important for patenting in service industries, skills are relatively more important for patenting in manufacturing. Both cooperation on innovation and purchasing of R&D services from external providers are also positively related to innovating and patenting.

When analysing productivity, I find that ICT is strongly associated with productivity (independently of the model specification) and relatively more important than R&D. The results provide evidence of the importance of product innovation for productivity in manufacturing and of process innovation for productivity in service industries, with organisational innovation being an important supplement to these two types of innovation. However, the results do not provide any strong evidence of the importance of marketing innovation for productivity, since it only has a positive impact in combination with product innovation in manufacturing. Although I used a simple measure for the skill composition of the workforce, its inclusion in regressions substantially affected the predictive power of R&D and slightly affected the predictive power of ICT, indicating possible complementarities of the skill variable with R&D. As to the relationship between R&D and ICT, they seem to be neither complements nor substitutes and, hence, exert their impacts on productivity through different channels.

To sum up, I find 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 the high rate of ICT diffusion in Norway could play an important role in explaining the ‘Norwegian productivity puzzle’, i.e. the fact that Norway, despite having a relative low level of R&D intensity, is one of the most productive OECD countries.

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Appendix A. Data sources

R&D statistics: The R&D statistics are survey data collected by Statistics Norway every second year up to 2001, and annually after that. These data comprise detailed information about firms' R&D activities and, in particular, about total R&D expenses divided between own 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 2001, 2004, 2006, 2008 and 2010 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 preceding each survey. In each wave, the sample is selected using a stratified sampling method for firms with 10–50 employees, whereas all firms with more than 50 employees are included. The strata are based on industry and firm size. Each survey contains about 5 000 firms (6 000 in the most recent surveys), although not all of them provide complete information.

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

The Investment statistics: The term 'Investment 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, provided 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, these data have comprised information about annual investments in hardware (purchased) and software (both purchased and on own account). The Investment statistics are organised according to the Standard Industrial Classification SN2002 (SN2007 since 2007)[40] and are collected for the following industries (NACE-codes from SN2002 in brackets):

- Manufacturing (NACE 15-37)
- Building and construction (NACE 45)
- Wholesale trade (NACE 51)
- 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).

[40] Since I have codes from both SN2002 and SN2007 for CIS2008 data, I use NACE codes from SN2002 in my analysis in order to avoid as far as possible the misspecification of a firm's industry (that is possible when one starts using a new classification).

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'. It corresponds in general to the concept of a company. A firm can consist of one or more establishments that 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, and, in particular, information about operating revenues, operating costs and operating profit/loss, 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) contains information about each individual employee's contract start and end, wages and contract working hours. Since both the firm identification number and the personal identification number are included, these data can easily be aggregated to the firm level.

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. I use this data set to obtain information on 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.

Table A1: Distribution across industries of the final sample (14 533 observations)

Industry:	NACE (SN2002)	Number of obs.	Share of obs.(%)
Mining and extraction	10-14	167	1.1
Manufacturing:	15-36	6199	42.7
Food products and beverages	15	834	5.7
Textiles	17	198	1.4
Other textile products	18-19	97	0.7
Wood and wood products	20	445	3.1
Pulp, paper and paper products	21	123	0.9
Publishing and printing	22	655	4.5
Chemicals and chemical products	24	244	1.7
Rubber and plastic products	25	210	1.4
Other non-metallic mineral products	26	283	2.0
Basic metals	27	174	1.2
Fabricated metal products (excl. machinery)	28	669	4.6
Machinery and equipment	29	674	4.6
Electrical machinery	31	269	1.9
Computers, radio/TV and communication equip.	30,32	132	0.9
Medical, precision and optical instruments	33	247	1.7
Motor vehicles and trailers	34	158	1.1
Other transport equipment	35	443	3.1
Furniture	36	344	2.4
Construction	45	1791	12.3
Service industries:	51-74	6143	42.3
Wholesale trade	51	1854	12.8
Land transport	60	505	3.5
Water and air transport	61-62	319	2.2
Supporting and auxiliary transport activities	63	483	3.3
Post and telecommunications	64	250	1.7
Computers and related activities	72	1288	8.9
Research and development	73	116	0.8
Other business-related services	74	1342	9.2
Other industries	37,40,41,90-92	219	1.5
Total		14533	100

Table A2: Descriptive statistics on key variables for the final sample (14533 observations)

Variable	Mean	Std. Dev.	Min	Median	Max
Value added (VA) per employee	610.021	380.685	65.940	525.999	4878.422
Number of employees	92.639	318.714	5	30	18815
Firm age	17.479	15.556	0.5	14	116
ICT capital services per VA	0.034	0.094	0	0.015	3.505
Tangible capital services per VA	0.060	0.107	0	0.025	3.257
Share of high-skilled	0.289	0.267	0	0.185	1
Part of a group (dummy)	0.617	0.486	0	1	1
Market location: local/regional (dummy)	0.516	0.499	0	1	1
Market location: national (dummy)	0.331	0.470	0	0	1
Market location: European (dummy)	0.091	0.287	0	0	1
Market location: world (dummy)	0.062	0.241	0	0	1
Cooperation in innovation (dummy)	0.169	0.375	0	0	1
Purchased R&D (dummy)	0.133	0.339	0	0	1
R&D investors, R>0 (dummy)	0.301	0.459	0	0	1
ICT investors, ICT>0 (dummy)	0.893	0.309	0	1	1
R&D intensity for R&D investors	32.519	101.183	0	0	1800.871
ICT intensity for ICT investors	21.093	77.369	0	7.437	3027.445
Any type of innovation (dummy)	0.479	0.499	0	0	1
Applied for a patent (dummy)	0.101	0.301	0	0	1
Number of patent applications	0.209	1.601	0	0	76

Table A3: Correlations between key variables, firms with positive R&D (4377 observations)

	Y/L (log)	*R/L* (log)	*ICT/L* (log)	*inno*	*sum-pat*	*L* (log)	*h*	Market location	Part of a group	Receive subsidy	Coop.	Purch. R&D
VA per emp. (log)	1											
R&D intensity (log)	0.09	1										
ICT intensity (log)	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							
Employment (log)	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

Appendix B. Definitions and examples of different types of innovation

The Oslo 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.’ (OECD, 2005, p. 46)

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 (OECD, 2005, p. 48). Design changes that 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 that 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 (OECD, 2005, p. 49). For example, the 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 between a product and process innovation. The Oslo Manual (OECD, 2005, p. 53) contains the following guidelines for distinguishing 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 in the firm’s business practices, workplace organisation or external relations. It requires more than mere organisational change or restructuring. In fact, the organisational method must not previously have been used by the business and must be the result of strategic decisions taken by management (OECD, 2005, p. 49). 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 subcontracting for the first time (OECD, 2005, p. 52).

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 previously have been 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 (OECD, 2005, p. 50).

Appendix C. Different issues concerning the model estimation

Table C1. Sample selection model for R&D and ICT choice (all firms).

	(1)^		(2)~	(3)^		(4)~
Dependent variable:	Dummy for R>0	log(R&D per emp.)	log(R&D per emp.)	Dummy for ICT>0	log(ICT per emp.)	log(ICT per emp.)
Employment (log)	0.104	-0.765***	-0.666***	0.518***	0.091*	0.091*
	[0.063]	[0.096]	[0.094]	[0.063]	[0.051]	[0.051]
Employment squared (log)	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: European	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 on 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-square or F-test for age dummies	58.80***		0.51	20.23**		1.90*
Chi-square or F-test for industry dummies	828.21***		20.30***	2419.54***		80.18***
Chi-square or F-test for regional dummies	23.54**		2.43**	53.49***		8.13***
Chi-square or F-test for time dummies	165.66***		2.29*	765.45***		237.19***
Correlation coefficient rho	-0.239***			-0,003		
Chi-square 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 2004, Wholesale industry (NACE 51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
^ Estimated by full maximum likelihood using the Heckman procedure in Stata; ~ estimated by OLS.
¤ A dummy for the positive R&D investment in any of the three previous years in model (1) and a dummy for positive ICT capital lagged two years in model (3).
*** p<0.01, ** p<0.05, * p<0.1

Table C2: Robustness checks for inclusion of the skill variable in the innovation output equation (by industry)

Sample:	All firms			Manufacturing			Services		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Predicted R&D intensity (log)	0.878***	0.836***	0.773***	0.860***	0.803***	0.762***	0.850***	0.812***	0.685***
	[0.042]	[0.043]	[0.049]	[0.061]	[0.063]	[0.070]	[0.062]	[0.062]	[0.077]
Interaction of predicted R&D and skilled share			0.169**			0.177			0.239***
			[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]
ICT intensity (log)	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]
Employment (log)	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]
Employment squared (log)	-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: Scandinavia	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: EU	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 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Probit model estimates for having at least one innovation.
*** p<0.01, ** p<0.05, * p<0.1.

Table C3: 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	Lagged	Predicted	Observed	Lagged	Predicted
Predicted R&D intensity (log)	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]
ICT intensity (log)	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]	
Employment (log)	0.749***	0.769***	0.340***	1.145***	1.144***	0.597**
	[0.059]	[0.060]	[0.104]	[0.153]	[0.165]	[0.264]
Employment squared (log)	-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: Scandinavia	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: EU	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	-7830.13	-7609.64	-7816.44	-4724.49	-4604.62	-4726.01
Number of observations	14533	14164	14533	14533	14164	14533
Number of non-zero obs.	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 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
^ Estimated by maximum likelihood as a probit model; ~ Estimated by pseudo maximum likelihood as a zero-inflated negative binomial count data model.
*** p<0.01, ** p<0.05, * p<0.1.

Table C4: Estimation results - Innovation output: Four types of innovation (all firms)

Innovation type:	New product		New process		Organisational		Marketing	
	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.	Coeff.	S.e.
All firms (14533 observations, 8554 firms)								
Predicted R&D intensity (log)	0.895 ***	0.043	0.541 ***	0.041	0.246 ***	0.039	0.387 ***	0.038
Share of high-skilled	0.694 ***	0.084	0.036	0.082	0.245 ***	0.082	0.277 ***	0.076
ICT intensity (log)	0.054 ***	0.012	0.042 ***	0.012	0.044 ***	0.011	0.022 **	0.011
Zero ICT investment	-0.107 **	0.054	-0.123 **	0.053	-0.057	0.053	-0.110 **	0.048
Employment (log)	0.565 ***	0.063	0.317 ***	0.062	1.141 ***	0.059	0.345 ***	0.055
Employment squared (log)	-0.014 *	0.007	0.000	0.007	-0.086 ***	0.007	-0.016 ***	0.006
Cooperation: National	0.509 ***	0.046	0.485 ***	0.043	0.359 ***	0.042	0.438 ***	0.041
Cooperation: Scandinavia	0.178 **	0.073	0.300 ***	0.064	0.225 ***	0.060	0.230 ***	0.061
Cooperation: EU	0.130 *	0.074	-0.081	0.065	0.064	0.063	0.041	0.064
Cooperation: World	-0.089	0.085	-0.016	0.076	0.025	0.069	-0.001	0.070
Purchased R&D	0.520 ***	0.044	0.362 ***	0.042	0.214 ***	0.040	0.208 ***	0.041
Number of non-zero obs.	4189		3118		3145		3748	
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^	3504.4 ***							
Log likelihood	-24017.1							

Notes: All regressions include a constant, firm age, industry, location and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors are robust to heteroscedasticity and clustered at the firm level.

Dependent variables: binary indicators for different types of innovation. Estimated as a quadrivariate probit model using the program *mvprobit* in Stata (see Cappellari and Jenkins, 2003) with the number of draws for the GHK simulator equal to 120.

^ This is the test that all correlations $\rho_{jk} = \rho_{kj}$ between η^k and η^j in (3b´), $j, k = 1, 2, 3, 4$ and $j \neq k$, are jointly equal to zero.

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

Table C5: Predicted propensities from the quadrivariate probit (QP) knowledge production function (by industry)

	All firms		Manufacturing		Services	
Combinations*	Observed frequencies	Predicted Mean	Observed frequencies	Predicted Mean	Observed frequencies	Predicted Mean
QP1111	0.0527	0.0593	0.0644	0.0725	0.0548	0.0599
QP1110	0.0202	0.0217	0.0268	0.0273	0.0171	0.0204
QP1101	0.0411	0.0384	0.0513	0.0463	0.0433	0.0442
QP1011	0.0246	0.0242	0.0318	0.0304	0.0241	0.0251
QP0111	0.0103	0.0107	0.0113	0.0110	0.0112	0.0116
QP0011	0.0266	0.0224	0.0231	0.0197	0.0303	0.0254
QP0101	0.0089	0.0088	0.0102	0.0113	0.0098	0.0094
QP0110	0.0189	0.0149	0.0197	0.0163	0.0176	0.0133
QP1001	0.0441	0.0418	0.0552	0.0540	0.0470	0.0430
QP1010	0.0150	0.0120	0.0186	0.0167	0.0158	0.0118
QP1100	0.0338	0.0309	0.0365	0.0356	0.0386	0.0332
QP0001	0.0495	0.0616	0.0510	0.0625	0.0524	0.0660
QP0010	0.0482	0.0607	0.0411	0.0530	0.0456	0.0600
QP0100	0.0287	0.0383	0.0365	0.0454	0.0236	0.0355
QP1000	0.0568	0.0692	0.0732	0.0844	0.0566	0.0739
QP0000	0.5206	0.5156	0.4496	0.4451	0.5123	0.5034
Number of obs.	14333		6199		6145	
Number of draws	120		80		80	

*QP refers to the combinations of the Quadrivariate Probit model for four innovation types: product, process, organisational and marketing innovation, e.g. QP1001 refers to the combination [1,0,0,1], i.e. the firm has introduced both product and marketing innovations, but not the other two types of innovation.

Table C6: Estimation results – Productivity: with combinations of product, process and organisational innovation (by industry)

Sample:	All firms		Manufacturing		Services	
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 (log)	0.091***	[0.005]	0.101***	[0.006]	0.092***	[0.007]
Tangible capital intensity (log)	0.084***	[0.004]	0.086***	[0.005]	0.080***	[0.005]
Share of high-skilled	0.357***	[0.040]	0.376***	[0.062]	0.521***	[0.041]
Employment (log)	0.069**	[0.033]	0.081**	[0.038]	0.054	[0.048]
Employment squared (log)	-0.005	[0.003]	-0.002	[0.004]	-0.007	[0.005]
R-squared	0.30		0.36		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 2004, 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 (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
TP refers to the combinations of the Trivariate Probit model for three innovation types: product, process and organisational innovation, e.g. TP101 refers to the combination [1,0,1], i.e. the firm has introduced both product and organisational innovations, but not process innovation.
*** p<0.01, ** p<0.05, * p<0.1

Table C7. Performing formal R&D and ICT: complementarity tests for productivity (all firms)

R&D and ICT variables:	(1) Both actual	(2) Both predicted	(3) R&D predicted, ICT invest. actual	(4) R&D predicted, ICT capital actual
R&D intensity (log)	0.017**	-0.100***	0.050***	0.036**
	[0.007]	[0.034]	[0.015]	[0.016]
ICT intensity (log)	0.078***	0.702***	0.047***	0.082***
	[0.004]	[0.077]	[0.012]	[0.015]
R&D*ICT	-0.001	-0.018**	0.009**	0.009*
	[0.002]	[0.008]	[0.004]	[0.004]
Tangible capital intensity (log)	0.089***	0.098***	0.089***	0.076***
	[0.004]	[0.004]	[0.004]	[0.004]
Employment (log)	0.125***	-0.045	0.171***	0.148***
	[0.020]	[0.034]	[0.020]	[0.020]
Employment squared (log)	-0.009***	0.002	-0.011***	-0.009***
	[0.002]	[0.003]	[0.002]	[0.002]
Number of observations	14533	14533	14533	14427
R-squared	0.25	0.23	0.26	0.27

Notes: All regressions include a constant, firm age, industry and location, and time dummies. Reference group: Local/regional market location, year 2004, Wholesale industry (NACE51), mature firms (16 years old or older) in the capital region (Oslo and Akershus). The standard errors [in brackets] are robust to heteroscedasticity and clustered at the firm level.
Dependent variable: Value added per employee (log). Estimated by OLS.
*** p<0.01, ** p<0.05, * p<0.1

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