

# WORK IN PROGRESS

## ICT and Innovation

Michael Polder (Statistics Netherlands)

Pierre Mohnen (Maastricht University)

George van Leeuwen (Statistics Netherlands)

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### Abstract

We investigate with Dutch micro data whether ICT investment boosts total factor productivity, whether it does so because it increases the return to R&D, and whether ICT requires organizational innovations to increase productivity.

Keywords: Innovation, ICT, R&D, productivity.

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\* Statistics Netherlands, Den Haag (NL)

† University of Maastricht, Maastricht (NL)

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## 1. Introduction

The digital revolution based on the information and communication technology (ICT) is in the eyes of most historians of science and technology classified among the general purpose technologies like the wheel, the steam power, the combustion engine and electricity (Lipsey, Carlaw and Bekhar, 2005; Brynjolfsson and McAfee, 2014; Gordon, 2016). It took some time before ICT showed up in the statistics of productivity. By now, capital is commonly split into ICT and non-ICT capital, and a great deal of total factor productivity growth in the last 30 years has been ascribed to ICT capital deepening. One explanation for the differential success of ICT capital in fostering productivity has been the argument of complementarity between ICT capital and organizational innovation. Firms need to reorganize their way of operating to benefit from the digital technology. But beyond its contribution to total factor productivity via ICT-capital deepening and organizational change, ICT can also increase the returns to R&D and generate a string of new technological innovations.

In this paper we shall reassess the contribution of ICT capital deepening to TFP growth and reexamine the complementarity hypothesis between organizational innovation and ICT. But our most important contribution will be to explore whether product/process innovation on the output side is ICT-facilitated in the sense that ICT makes many innovations possible.

The data we use are sourced from different surveys at Statistics Netherlands, which are linked at the firm level. The sample includes firms in the manufacturing sector (NACE Rev. 1.2 15 to 37) and in the services sector (NACE Rev. 1.2 50 to 93). The innovation variables are sourced from the Community Innovation Survey (CIS) from which we pool the data from three biannual innovation survey waves starting in 2004. Information on ICT usage comes from the annual E-commerce survey. Finally, production data (production value, factor costs, and employment) are taken from the Production Statistics. We use industry price information at the lowest available level from the Supply and Use tables.

The paper is structured as follows. In section 2, we briefly review the literature on the role of ICT on productivity, on the complementarity between ICT and organizational change and on the GPT aspects of ICT. Section 3 is devoted to modeling aspects. We outline the present model and possible alternative models. In section 4 we describe the data and the main variables. In section 5 we present first estimation results and in section 6 preliminary conclusions.

## 2. The literature

A vast literature has estimated the returns (private and social) to R&D and the contribution of R&D to total factor productivity or economic growth (see e.g. Hall, Mairesse and Mohnen, 2013). Another branch of literature has related R&D to innovation and innovation to productivity (see e.g. Mairesse and Mohnen, 2013). Both of these strands of literature do not include the effects of ICT. In parallel, many studies have investigated the effect of the adoption of information and communication technology (ICT) equipment on total factor productivity (see e.g. Stiroh, 2010). Some studies have used aggregate or sectoral data, others have used firm data. The studies that use macro or sectoral data have mainly analyzed the effect of ICT or R&D on productivity within a growth accounting framework (see Biagi (2013) for a review), but not so much the complementarity between ICT and R&D in raising productivity. A substantial effort has been made to measure the stocks of intangibles, including R&D but also software, databases and organizational capital, and to assess their importance in corrected GDP growth (Corrado, Hulten and Sichel, 2009; Corrado, Haskel, Jona-Lasinio and Iommi, 2013).

Another line of literature underscores the complementarity between ICT and organizational innovation (starting with Brynjolfsson and Hitt, 2000). Case studies reveal that the introduction of information technology is combined with a transformation of the firm, investment in intangible assets, and a change in the relation with suppliers and customers. Electronic procurement, for instance, increases the control of inventories and decreases the costs of coordinating with suppliers. In addition, ICT offers the possibility for flexible production: just-in-time inventory management, enterprise resource planning, et cetera. The available econometric evidence at the firm level shows that a combination of investment in ICT and changes in organizations and work practices facilitated by these technologies contributes to firms' productivity growth. The empirical studies that have been conducted on the complementarity hypothesis are mainly based on micro data (Bresnahan, Brynjolfsson and Hitt, 2002; Black and Lynch, 2001; Caroli and Van Reenen, 2001; Brynjolfsson et al., 2006; Crespi et al., 2007; Van Reenen et al., 2010; Riley and Vahter, 2013). In this work, information technology is seen to enable organizational investments (business processes and work practices), which in turn lead to cost reductions and improved output and, hence, productivity gains. Invest-

ment in ICT can therefore be considered as a separate input into the innovation process, which can lead to new services (e.g. internet banking), new ways of doing business (e.g. B2B), new ways of producing goods and services (e.g. integrated management) or new ways of marketing (e.g. electronic cataloguing).

Whereas there is a lot of empirical backing at the firm level for the complementarity between ICT and organizational innovation there is less evidence of a complementarity between R&D and ICT or between ICT and technological innovations in the form of new products or processes (see Cerquera and Klein, 2008; Hall, Lotti and Mairesse, 2012; Polder et al., 2009). Spiezia (2011) also concludes from the OECD-lead international comparison study on firm data that ICT does not increase the probability to come up with a new innovation developed in-house. A positive sign comes from the Eurostat ICT impacts project (Eurostat, 2008). Because data on ICT investment are not available in the survey on ICT use it is proposed to use other metrics such as the share of PC enabled personnel, the adoption of broadband and e-commerce variables as indicators for firm-level ICT-intensity. Van Leeuwen and Farooqui (2008, Chapter 12 of the Eurostat report) show that e-sales and broadband use affect productivity significantly through their effect on innovation output. Broadband use only has a direct effect on productivity if R&D is not considered in the model as an input to innovation.

Also at the industry-level the complementarity between R&D and ICT is beginning to be explored. Using cross-country industry-level growth accounting datasets including ICT and intangibles, Chen, Niebel and Saam (2014) and Corrado, Haskel and Jona-Lasinio (2014) find evidence of a positive direct effect of ICT on TFP, as well as a significant indirect effect through its interaction with intangibles. However, in a similar exercise Polder (2015) fails to replicate these results for the Netherlands, suggesting that there might be cross-country differences.

### **3. Model**

The modeling approach follows Hall, Lotti and Mairesse (2012) in that we consider 4 strategies (innovating in products, in processes, in organizational changes and adopting e-commerce), and that productivity is made dependent on the choice of combination of strategies. It is an extension of the Crépon-Duguet-Mairesse (1998) model. But there are also some

differences with respect to Hall et al. (2012). Most importantly, we allow for simultaneous feedback effects between the various forms of innovation to be able to assess complementarities at the adoption stage. Second, we do not estimate an R&D equation but consider R&D to be pre-determined. It is measured as a binary variable indicating whether the firm is a continuous R&D performer, which indicates the existence of past R&D performance. Third, since product and process innovation may include ICT aspects, in which case any complementarity with ICT is to some extent spurious, we have decided to use increase in electronic commerce as a measure of ICT innovation. E-commerce takes value 1 if either the proportion of e-purchases in total purchases or the proportion of e-sales in total sales increases compared to the previous year. Fourth, in the productivity equation we do not let the current choices of strategy combinations affect current productivity growth but instead we assume that the past choices of strategy combinations matter. This one-year lag follows the Markov chain modeling of productivity growth and the influence of R&D on unobserved productivity in Doraszelski and Jaumandreu (2013).

### 3.1. Innovation outputs: product, process, organizational and ICT innovations

In order to test for the presence of complementarity between the four strategies, in particular between ICT (e-commerce) and the three types of innovation, our first method is based on the adoption approach, i.e. the detection of joint use of strategies for reasons other than correlations in its unobserved determinants. This approach was used by Miravete and Pernías (2006), Bartelsman, van Leeuwen and Polder (2017) and van Leeuwen and Mohnen (2017). Let us denote each of the four strategies as  $y_j$ ,  $j=1, \dots, 4$ . Suppose an objective function e.g. productivity that depends on the realization of the four strategies. The productivity achieved by the adoption of each individual strategy  $P_{it}^j$  ( $j = 1, \dots, 4$ ) is given by the following expression

$$P_{it}^j = \left( \beta_j' x_{it}^j + \sum_{k \neq j} (\alpha_{jk}/2) y_{it}^k + \varepsilon_{it}^j \right) y_{it}^j.$$

For reasons of identification,  $\alpha_{jk} = \alpha_{kj}$ . The  $\varepsilon_{it}^j$  are assumed to be jointly normally distributed with unitary variances but non-zero covariances. The “return” from the adoption of strate-

gy  $j$  depends on the realization of some exogenous variables, which may be strategy specific, the adoption of the other strategies and a random error term. Total productivity is given by

$$TP_{it} = \sum_j P_{it}^j y_{it}^j.$$

As shown by Lewbel (2007), this way of writing the objective function avoids any incoherency and incompleteness problem.

To illustrate, suppose there are only two strategies. If the combination of strategies 1 and 2, i.e. state (1,1), was chosen, then the value of total productivity would be

$$TP_{it}(1,1) = \beta_1' x_{it}^1 + \alpha_{12} + \beta_2' x_{it}^2 + \varepsilon_{it}^1 + \varepsilon_{it}^2.$$

The coefficient  $\alpha_{12}$  captures the complementarity (if positive) or substitutability (if negative) between the pair of strategies. For every combination of strategies we could compute the value of the objective function. To estimate the parameters of the model we write down the probability that every possible combination of strategies is chosen. This probability is derived from the upper and lower bounds of the distribution of the error terms given that the value of the objective function under (1,1) must be higher than under any pair of strategies:

$$\begin{aligned} TP_{it}(1,1) \geq TP_{it}(0,0) &\Rightarrow \beta_1' x_{it}^1 + \alpha_{12} + \beta_2' x_{it}^2 + \varepsilon_{it}^1 + \varepsilon_{it}^2 \geq 0 \\ TP_{it}(1,1) \geq TP_{it}(1,0) &\Rightarrow \beta_1' x_{it}^1 + \varepsilon_{it}^1 \geq 0 \\ TP_{it}(1,1) \geq TP_{it}(0,1) &\Rightarrow \beta_2' x_{it}^2 + \varepsilon_{it}^2 \geq 0. \end{aligned}$$

The choice (1,1) is therefore associated to the likelihood that  $\varepsilon_{it}^2 \geq L_1 = -\beta_2' x_{it}^2$  and that  $\varepsilon_{it}^1 \geq L_2 = \max(-\beta_1' x_{it}^1, -(\beta_1' x_{it}^1 + \alpha_{12} + \beta_2' x_{it}^2 + \varepsilon_{it}^2))$ , in other words to  $\int_{L_1}^{\infty} \int_{L_2}^{\infty} \varphi(\varepsilon_{it}^1, \varepsilon_{it}^2) d\varepsilon_{it}^1 d\varepsilon_{it}^2$ . The same reasoning can be held to derive the likelihood for every other pair of strategies. The same logic holds for four strategies in which case a chosen pair necessitates 15 comparisons of values of the likelihood function. The parameters can be estimated by maximum simulated likelihoods (see Train, 2003). Standard errors of the estimates are computed by bootstrapping.

### 3.2. Production function

We measure productivity as value added over employment. Assume a Cobb-Douglas production function with two inputs, labor and capital.<sup>1</sup> Let us denote log transformed variables by small letters. Hence  $q$ ,  $l$ , and  $c$  represent respectively the log of value added, labor and capital stock. Labor productivity is given by

$$q_{it} = \alpha_0 + \alpha_L l_{it} + \alpha_C c_{it} + \omega_{it} + v_{it}$$

where  $\omega_{it} = g(\omega_{it-1}, \sum_j \alpha_y^j y_{it-1}^j) + \xi_{it}$ .

The term  $\omega_{it}$  represents the productivity that is known to the firm when it makes its input and investment decisions but unknown to the econometrician. It is assumed to follow a first-order Markov process and to depend on the 16 combinations of innovation strategies. The last term represents random technological shocks, which are distributed iid  $N(0, \sigma_v^2)$ . The productivity equation is estimated by GMM as proposed by Akerberg, Caves and Frazer (2015). Lagged values of log transformed labor and capital/labor ratios are used as instruments.

### 4. Data

The data used in this exercise are sourced from different surveys at Statistics Netherlands, which are linked at the firm level. The sample includes firms in the manufacturing sector (NACE 15 to 37) as well as the services sector (NACE 50 to 93).<sup>2</sup> The innovation variables are sourced from the Community Innovation Survey (CIS). We pool the 2004, 2006, and 2008 editions.<sup>3</sup> Information on ICT usage comes from the E-commerce (EC) survey. Finally, production data (production value, factor costs, and employment) are taken from the Produc-

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<sup>1</sup> At a later stage we shall split capital into ICT and non-ICT capital.

<sup>2</sup> We exclude NACE 73, the commercial R&D sector.

<sup>3</sup> We plan to add one or two waves to the present dataset. The 2002 wave could not be used because prior to 2002 there was no data on electronic commerce, so no way to calculate a change in the use of e-commerce.

tion Statistics (PS). We use price information at the lowest available level from the Supply and Use tables (AGT); this results in deflators at a mixed 4-digit and 3-digit NACE levels.

Our definitions of the different innovation types follow those in the innovation survey. Thus, product innovation is defined as a new or (significantly) improved good or service. Process innovation is defined as a significantly improved method of production or logistics, or supporting activities such as maintenance and operations for purchasing, accounting, or computing. Finally, organizational innovations include the introduction of new business practices, knowledge management systems, methods of workplace organization (i.e. system of decision making), and management of external relations. In all cases, the innovation needs to be new to at least the firm, and may be developed by the firm itself or by another enterprise (or in collaboration). For each of these innovation types, the CIS provides information on whether a firm stated to have performed such an innovation or not in the three-year period ending in the year preceding the survey (for example, the CIS 2006 is carried out in 2007 and concerns the period 2004 to 2006). As mentioned above, ICT innovation is characterized by an increase in the use of e-commerce and is sourced from the EC survey.

Table 1 gives the summary statistics by sector for the key variables used in the analysis, for the different samples used in the different equations. The knowledge production function uses CIS and EC data whereas the TFP equation uses PS, CIS and EC. The overall impression is that the means of the variables are pretty much in line in the various samples. Based on the employment variables, however, it seems that crossing the CIS with the E-commerce survey leads to a bias towards larger firms. This is not surprising since the sampling frame of the latter survey is relatively small, and smaller firms are less likely to be sampled in all surveys, so that in crossing data sets these firms have a higher probability to drop out. There are, however, some differences between manufacturing and services. Firms in the services sector are much less likely to have their main market abroad. They also cooperate less in innovative activities, and less firms receive funding. On the other hand, services firms have a higher intensity of broadband use. They are less likely to do R&D than manufacturing firms, but are more prone to use electronic sales or purchases. Thus, compared to firms in manufacturing, services firms appear to be more domestically oriented, relying relatively more on ICT and private funding for innovation.



Table 2 shows the distribution of possible combinations of innovation types for the combined CIS and EC sample. Overall, the manufacturing sector seems more innovative: here only 23% of the firms report not to have been innovative, against 38% in the services (this category does include firms with an ongoing or abandoned innovation project, however). A greater proportion of firms in services than in manufacturing do only product innovation or only process innovation. Whereas services firms are more likely to use e-commerce than manufacturing firms, their tendency to be innovative in the use of e-commerce is lower than in manufacturing. In other words, they have been early adopters of e-commerce but have not increased so much their use of e-commerce after that. The simultaneous adoption of process, organizational and ICT innovation as well as the joint adoption of all innovations at once are more prevalent in manufacturing than in services. Every combination of innovation strategies is observed in at least 1% of the cases.<sup>4</sup>

## 5. Results

In this section, the estimation results of the two parts of the model, the strategy choices and the augmented production function are presented. Since one may expect that the importance

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<sup>4</sup> One could be concerned with the ability of firms to dissociate process and organizational innovations. Crespi et al. (2007), for example, worry that (what firms mark as) process innovation in fact incorporates ‘disembodied’ reorganization such as contracting out, new working methods etc. Greenhalgh and Rogers (2010, ch. 1) include organizational innovation in their definition of process innovation. In this case one would expect that firms would tick the boxes for both process and organizational innovation. The distribution of innovation mode combinations suggests that this is not a big problem in our data. A quick calculation shows that process or organizational occur together in only 19.7% of the observations. This suggests that firms do not view these types of innovation as the same thing. In addition, the correlation in the CIS sample between process and organizational innovation is 0.27, which is in fact lower than the correlations between product and process and between product and organizational innovation. Finally, some care has been taken in the survey to caution the respondents not to include organizational changes in the question on process innovation (the closing sentence of the question reads “Exclude purely organizational innovations”).

of innovation modes can differ between industries, we present the estimation results separately for manufacturing and services.<sup>5</sup>

### 5.1 Innovation output

In tables 3a and 3b we report the marginal effects of the explanatory variables on the probability of performing each of the four innovation innovation. For example, manufacturing firms that collaborate on innovation have a 32% higher chance to be product innovators. The quadrivariate simultaneous probit model is estimated by maximum likelihood and the standard errors of the estimates are bootstrapped.<sup>6</sup> Preliminary estimation results revealed that organizational and e-commerce innovations were not related to the presence of funding for innovation or the presence of R&D performance, and e-commerce is not related to collaboration on innovation.

It can be noticed that the marginal effects are more sizeable for product and process innovation than for organizational and e-commerce innovations. The two strongest determinants are the presence of R&D performance and collaboration on innovation. R&D performers are 48% more likely to be product innovators and 16% more likely to be process innovators in manufacturing. The corresponding marginal effects are 30.6% and 24.9% for firms in services. Firms with government funding for innovation are 7% to 20% more likely to be product or process innovators depending on the sector and the type of innovation. But these effects should be interpreted as correlations more than as causalities since all variables are measured contemporaneously.

An interesting result concerns the effect of broadband intensity (the percentage of broadband enabled workers). It makes a significant difference in services for all types of innovation and for organizational innovation in manufacturing. Broadband access allows firms to quickly

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<sup>5</sup> Industry differences may also be present within manufacturing and services. As far as this concerns industry specific averages, those are controlled for by industry dummies. Due to the smaller number of observations it is not possible to allow for varying effects of the variables of interest for the different sub-industries.

<sup>6</sup> When computing the marginal effects of the explanatory variables on the four innovations individually we proceed as if we had separate probits.

share and obtain information from other agents in the firm's network; following Eurostat (2008) it is seen as an indicator of how advanced the ICT infrastructure of a firm is. Our results show that ICT use is more important in services than in manufacturing. The positive correlation between broadband use and organizational innovation confirms the complementarity between ICT use and organizational change (Brynjolfsson and Hitt, 2000).

The most interesting results concern the complementarity between ICT innovations and non-ICT innovations. As stated in Eurostat (2008), e-commerce is seen as an indicator of how a firm actually uses its ICT infrastructure for selling goods and services and for purchasing inputs. We measure the presence of an increase in the use of e-commerce. In both manufacturing and services, the correlations between four types of innovation, irrespective of the correlations between the four error terms, are significant at the 1% level. Except for e-commerce and process innovations in manufacturing, they are all positive. The largest correlations are between product and process innovation, followed by organizational and product or process innovations. New products often require new production methods and reorganizations in the operations of the firm. The correlations of e-commerce with product and process innovations could reflect the fact that some new products and processes are ICT-related and offer some support to the hypothesis that ICT leads to further innovations.

## **5.2. Productivity**

In tables 4a and 4b, we present the estimation of the production function for manufacturing and services firms. We use value added over employment as the dependent variable. We present two types of estimates, first an OLS estimation of the Cobb Douglas production function and then a GMM estimation following Akerberg, Caves and Frazer (2015). In the OLS estimated model, the 15 innovation combination dummies are part the TFP expression. They indicate differences in TFP compared to the reference category (absence of any type of innovation). No attempt is made to correct for the endogeneity of capital and labor. The dummies are lagged by two years (corresponding to one wave) and therefore pre-determined. The second model corresponds to the one described in section 3, where the combination dummies are now part of the unobserved random productivity that the decision maker knows. Labor and capital are instrumented by their lagged values and the combination dummies are again considered as pre-determined. Two-digit industry and year effects are controlled for by dummies (but not reported). The signs and magnitudes of the estimated coefficients are not

very different between the two estimation methods. We shall rely on the GMM estimates as it handles the endogeneity of labor and capital and leads to some more significant combination dummy coefficients than the OLS model.

Somewhat surprisingly, in manufacturing, process innovation alone, process and organizational innovation and organizational innovation and e-commerce innovation (all in the absence of product innovation) lead to lower productivity two years later than in the absence of any innovation at all. In services, this negative effect of innovation is also visible for the combination of process and organizational innovation. These results suggest that change in the production methods, especially when combined with changes in the organization of work, lead in the short term to lower productivity. One explanation could be adjustment costs. In contrast, product innovations, especially when combined with other innovations, lead to productivity gains compared to the no innovations at all scenario.

### 5.3. Testing for complementarity and substitutability of innovation modes

It is possible to test formally the complementarity and substitutability between the different innovation modes. Following the approach taken by Mohnen and Röller (2005) we apply a test for super- and submodularity of the production function. If the production function is supermodular with respect to a combination of innovation modes, this is evidence of the complementarity of these modes. In the case of submodularity, the modes are substitutes.

In the presence of 4 strategies, strategies 1 and 2 are complementary if the following restriction holds on the parameters associated with the combinations:

$$\beta_{01ab} + \beta_{10ab} - \beta_{11ab} - \beta_{00ab} \leq 0$$

whatever values 0 or 1 a and b take for the other 2 strategies. Hence for every pair of strategy there are 4 inequality restrictions. The inequalities for substitutability are easily obtained by replacing ‘ $\leq$ ’ with ‘ $\geq$ ’. Kodde and Palm (1986) derive a Wald test-statistic for testing these inequality restrictions. Let  $\gamma$  be the 16x1 vector of coefficients on the combination dummies in the augmented production function. The test statistic is given by

$$D = (S\tilde{\gamma} - S\hat{\gamma})'(S' \text{cov}(\hat{\gamma})S)^{-1}(S\tilde{\gamma} - S\hat{\gamma})$$

where

$$\tilde{\gamma} = \arg \min (S\gamma - S\hat{\gamma})'[S' \text{cov}(\hat{\gamma})S]^{-1}(S\gamma - S\hat{\gamma}) \text{ s.t. } S\gamma \leq 0$$

where  $\hat{\gamma}$  the GMM estimate of  $\gamma$ ,  $\text{cov}(\hat{\gamma})$  is the estimated covariance matrix of  $\gamma$ , and  $S$  is a matrix that maps the coefficients into the constraints derived above.<sup>7</sup> The interpretation of  $\tilde{\gamma}$  is that it is the coefficient that is as close as possible to the unrestricted GMM estimates under the restrictions reflected in  $S$ . We use quadratic minimization under inequality constraints in MATLAB to calculate  $\tilde{\gamma}$ . Critical values for the test statistic  $D$  can be found in Kodde and Palm.<sup>8</sup>

Tables 5a and 5b report the results of the tests of complementarity and substitutability for every pair of innovation strategies in manufacturing and in services. Complementarity is not rejected at the 5% level for product and process innovations, product and organizational innovations, process and e-commerce innovations, and organization and e-commerce innovations in manufacturing. Correspondingly, substitutability is rejected for all these pairs of strategies at the 5% level (and at the 10% level for organizational and e-commerce innovations). For process and organizational innovations, and process and e-commerce innovations in manufacturing, complementarity is rejected but substitutability is neither accepted nor rejected at the 5% level. For services the outcomes are very clear: wherever complementarity is not rejected, substitutability is, and vice versa. Product and process innovations are complementary with organizational innovations, and e-commerce innovation is complementary with process and organizational innovations.

In summary, the two tests of complementarity (tables 3 and 5) do not always coincide. Strategies might be adopted jointly but not necessarily with the aim of achieving higher productivity. There may be other objectives that make them coincide in order to reach higher outcomes. Nevertheless, they coincide in more than 50% of the cases. In particular, the hypothe-

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<sup>7</sup> Equivalently, let  $h(\beta)$  denote the vector of restrictions, such that  $H_0: h(\beta) < 0$  and  $H_1: h(\beta) \geq 0$  (i.e. in the restrictions above, bring all terms to the left-hand side). As in the notation of Kodde and Palm,  $S = \partial h / \partial \beta$ , a derivative matrix which consists only of elements -1, 0, and 1.

<sup>8</sup> For the lower bound of the test statistic, the number of degrees of freedom ( $df_{LB}$ ) equals the number of equality constraints plus 1, and the number of degrees of freedom for the upper bound ( $df_{UB}$ ) equals the total number of constraints. Since we have four inequality constraints, and no equality constraints,  $df_{LB} = 1$  and  $df_{UB} = 4$ .

sis of complementarity between organizational change and ICT is corroborated with both tests. With the second test, ICT through the use of e-commerce is also complementary to process innovations in both manufacturing and services. The complementarity between ICT and product innovations is rejected in both sectors.

## **6. Conclusions and further research**

In this paper, we investigate the relation between innovation and ICT. We consider three types of innovation not necessarily related to ICT– product, process and organizational innovation – and an additional innovation that reflects the use of ICT, namely the increase in the use of e-commerce. The intensity of broadband use is another variable measuring the use of ICT that we introduce among the explanatory variables. Lacking continuous measures for the output of process and organizational innovation, innovation output is measured by dichotomous variables reflecting whether a firm performed a particular type of innovation or not. First, we estimate the joint adoption of the four innovation variables, and in a second step we estimate the effect of the various combinations of those strategies on total factor productivity.

The hypothesis of complementarity between ICT and organizational innovations is strongly corroborated by our analysis of Dutch firm data. The two tests of complementarity confirm this finding as well as the positive correlation between the intensity of broadband use and organizational innovations. Less clearcut conclusions can be derived regarding the complementarity between ICT and technological (product or process innovations), which would confirm the general purpose technology characteristic of ICT.

Our results can also be related to findings at a higher aggregation level. Within the macroeconomic literature there is a longstanding debate on the causes of higher economic growth and the growth of productivity in the United States over the last two decades compared to the rest of the world, in particular the European Union (see e.g. van Ark et al. 2008, and Jorgenson et al. 2008). The most common explanation of this phenomenon is that the US have been more successful in investing and implementing new information and communication related technologies. Macroeconomic figures show that the European Union is behind in terms of the contribution to economic growth of ICT producing and using sectors (mainly market services) and of components related to the knowledge economy (quality of labor, ICT capital, and technological change). Our results connect and reinforce these observations since they

provide evidence that ICT inputs indeed lead to productivity differences at the micro-level *via* its impact on innovation, in particular changes in organization.

There are a number of issues that deserve further research. Firstly, since we have available various waves of the CIS, it is possible to introduce firm-specific effects. Among other things, this may make the results more robust to omitted variables and various other sources of bias (provided they are approximately time-invariant). In addition, it is possible to investigate dynamics. For example, current R&D expenditures may lead to innovation only after a period of time. Likewise, innovation may not immediately materialize into productivity gains. However, the introduction of feedback and/or autoregressive effects, especially in combination with fixed effects, is an econometrically challenging extension (e.g. Raymond et al. 2010). Finally, we had no data about worker skills. The availability of such a variable would allow us to test the additional the complementarity hypothesis between worker skills and ICT, which is also often reported in the literature.

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**Table 1. Summary statistics, 2004-2008**

	<b>manufacturing</b>	<b>N</b>	<b>services</b>	<b>N</b>	<b>Total</b>	<b>N</b>
Employment (fte)	227.87	2428	285.61	3661	262.59	6089
Value added per fte 1000s €	74.67	2424	109.75	3636	95.72	6060
Belonging to a group (%)	0.77	2428	0.66	3631	0.7	6059
Cooperation on innovation (%)	0.4	2428	0.16	3661	0.26	6089
Funding of innovation (%)	0.38	2428	0.07	3661	0.19	6089
Exporter (%)	0.84	2428	0.41	3631	0.58	6059
Foreignly owned (%)	0.39	2428	0.24	3661	0.3	6089
R&D performer (%)	0.47	2428	0.14	3661	0.28	6089
Share of e-purchases (%)	0.05	2428	0.08	3637	0.07	6065
Share of e-sales (%)	0.03	2428	0.04	3637	0.04	6065
Broadband usage (%)	0.39	2107	0.54	3199	0.48	5306

N=number of observations

**Table 2. Count of occurrences of combinations of innovation strategies, 2004-2008 (combined CIS and EC sample)**

<b>manufacturing</b>				<b>services</b>			
combinations	Freq.	Percent	Cum.	combinations	Freq.	Percent	Cum.
0000	509	23.13	23.13	0000	1,168	37.63	37.63
0001	157	7.13	30.26	0001	103	3.32	40.95
0010	73	3.32	33.58	0010	109	3.51	44.46
0011	175	7.95	41.53	0011	76	2.45	46.91
0100	142	6.45	47.98	0100	303	9.76	56.67
0101	87	3.95	51.93	0101	84	2.71	59.38
0110	68	3.09	55.02	0110	104	3.35	62.73
0111	335	15.22	70.24	0111	177	5.7	68.43
1000	169	7.68	77.92	1000	441	14.21	82.64
1001	78	3.54	81.46	1001	55	1.77	84.41
1010	30	1.36	82.83	1010	57	1.84	86.24
1011	74	3.36	86.19	1011	45	1.45	87.69
1100	62	2.82	89	1100	161	5.19	92.88
1101	40	1.82	90.82	1101	35	1.13	94.01
1110	40	1.82	92.64	1110	66	2.13	96.13
1111	162	7.36	100	1111	120	3.87	100
<b>Total</b>	<b>2,201</b>	<b>100</b>		<b>Total</b>	<b>3,104</b>	<b>100</b>	

Quadruplets of innovation types organized according to (Product, Process, Organizational, E-commerce), with 1 = yes and 0 = no

**Table 3a. Marginal effects for the knowledge production function: manufacturing**

<b>Manufacturing</b> <i>variable</i>	<i>PRODUCT</i>			<i>PROCESS</i>			<i>ORGANIZATIONAL</i>			<i>E-COMMERCE</i>		
	<i>me</i>	<i>sig</i>	<i>std err</i>	<i>me</i>	<i>sig</i>	<i>std err</i>	<i>me</i>	<i>sig</i>	<i>std err</i>	<i>me</i>	<i>sig</i>	<i>std err</i>
<i>product innovation</i>	--	--	--	0,171 ***		0,007	0,037 ***		0,009	0,043 ***		0,002
<i>process innovation</i>	0,174 ***		0,007	--	--	--	0,155 ***		0,008	-0,012 ***		0,002
<i>organizational innovation</i>	0,039 ***		0,005	0,162 ***		0,006	--	--	--	0,014 ***		0,001
<i>e-commerce innovation</i>	0,044 ***		0,005	-0,012 ***		0,003	0,013 **		0,006	--	--	--
<i>part of enterprise group</i>	-0,02 *		0,011	0,04 ***		0,01	0,019		0,013	-0,002		0,003
<i>foreignly owned</i>	0,002		0,005	0,023 ***		0,006	-0,016 **		0,007	0,006 ***		0,002
<i>exporter</i>	0,022 *		0,012	-0,002		0,01	0,051 ***		0,013	0,005 *		0,003
<i>cooperation on innovation</i>	0,32 ***		0,007	0,234 ***		0,006	0,044 ***		0,007	--	--	--
<i>funding for innovation</i>	0,221 ***		0,006	0,071 ***		0,006	--	--	--	--	--	--
<i>broadband intensity</i>	0,063		0,058	-0,041		0,026	0,156 ***		0,035	-0,003		0,013
<i>R&amp;D performer</i>	0,48 ***		0,007	0,163 ***		0,007	--	--	--	--	--	--
<i>high-tech industry</i>	0,035 ***		0,005	-0,113 ***		0,004	-0,026 ***		0,004	-0,014 ***		0,001
<i>medium-tech industry</i>	-0,03 ***		0,004	0,029 ***		0,004	-0,02 ***		0,005	-0,022 ***		0,002
<i>lagged employment</i>	0,013		0,079	0,009		0,07	0,046		0,087	0,008		0,021
N	1939											
Log likelihood	-5749,02											

Dependent variables: dummies for product, process, organizational and e-commerce innovation. Significance levels: \*\*\* = 1%, \*\* = 5%, \* = 10%, based on bootstrapped standard errors.

**Table 3b. Marginal effects for the knowledge production function: services**

**Services**

variable	PRODUCT			PROCESS			ORGANIZATIONAL			E-COMMERCE		
	me	sig	std err	me	sig	std err	me	sig	std err	me	sig	std err
product innovation	--	--	--	0,242 ***		0,004	0,093 ***		0,001	0,04 ***		0,001
process innovation	0,136 ***		0,01	--	--	--	0,175 ***		0,002	0,021 ***		0,001
organizational innovation	0,045 ***		0,012	0,174 ***		0,006	--	--	--	0,024 ***		0,002
e-commerce innovation	0,019		0,012	0,021 ***		0,007	0,024 ***		0,002		--	
part of enterprise group	0,05 *		0,026	0,014		0,013	0,031 ***		0,003	0,017 ***		0,004
foreignly owned	0,056 ***		0,011	-0,027 ***		0,005	0,017 ***		0,001	0,005 **		0,002
exporter	0,045 ***		0,017	0,082 ***		0,008	0,036 ***		0,002	0,024 ***		0,001
cooperation on innovation	0,31 ***		0,008	0,373 ***		0,005	0,053 ***		0,002		--	
funding for innovation	0,109 ***		0,009	0,076 ***		0,003	--	--	--		--	
broadband intensity	0,076 **		0,033	-0,02		0,023	0,101 ***		0,011	0,029 ***		0,011
R&D performer	0,306 ***		0,007	0,249 ***		0,003	--	--	--		--	
high-tech industry	0,157 ***		0,007	-0,128 ***		0,005	0,083 ***		0,002	-0,034 ***		0,001
medium-tech industry	0,028 *		0,015	0,011		0,009	0,03 ***		0,011	-0,064 ***		0,002
lagged employment	-0,004		0,192	0,019		0,1	0,034 ***		0,011	0,012		0,026
N	2684											
Log likelihood	-7831,55											

Dependent variables: dummies for product, process, organizational and e-commerce innovation. Significance levels: \*\*\* = 1%, \*\* = 5%, \* = 10%, based on bootstrapped standard errors.

**Table 4a Estimation of the augmented production function: manufacturing**

Dependent variable Method	OLS			log(real VA)					
	Est.	SE	signif	Est.	SE	signif	Est.	SE	Signif
	production function			production function			random productivity		
N	1770			1770					
Constant	3,271	0,07	***	3,001	0,027	***	0,493	0,012	***
log Capital (k)	0,255	0,012	***	0,249	0,006	***			
Log Labour (l)	0,794	0,019	***	0,786	0,009	***			
d0001 t - 1	0,002	0,057					-0,009	0,024	
d0010 t - 1	-0,08	0,057					0,003	0,024	
d0011 t - 1	-0,168	0,083	***				-0,11	0,035	***
d0100 t - 1	-0,055	0,066					-0,072	0,028	***
d0101 t - 1	0,088	0,103					-0,032	0,044	
d0110 t - 1	-0,299	0,07	***				-0,171	0,029	***
d0111 t - 1	0,024	0,088					0,023	0,037	
d1000 t - 1	0,014	0,053					0,023	0,022	
d1001 t - 1	-0,079	0,066					-0,025	0,028	
d1010 t - 1	-0,013	0,064					0,033	0,027	
d1011 t - 1	-0,074	0,088					0,041	0,037	
d1100 t - 1	0,013	0,048					0,055	0,02	***
d1101 t - 1	0,039	0,067					0,073	0,028	***
d1110 t - 1	0,035	0,041					0,024	0,017	
d1111 t - 1	0,003	0,05					0,055	0,02	***
industry dummies	yes			yes			yes		
year dummies	yes			yes			yes		
R2-adjusted	0,833								



**Table 4b Estimation of the augmented production function: services**

Dependent variable Method	log(real VA)								
	OLS production function			GMM production function			GMM random productivity		
	Est.	SE	signif	Est.	SE	signif	Est.	SE	signif
N	2509			2509					
Constant	4,044	0,065	***	3,001	0,026	***	1,297	0,011	***
log Capital (k)	0,285	0,01	***	0,28	0,006	***			
Log Labour (l)	0,578	0,014	***	0,57	0,008	***			
d0001 t - 1	0,007	0,038					-0,002	0,019	
d0010 t - 1	0,131	0,047	***				0,093	0,023	***
d0011 t - 1	-0,049	0,057					-0,026	0,028	
d0100 t - 1	-0,06	0,072					-0,018	0,035	
d0101 t - 1	0,055	0,086					0,042	0,042	
d0110 t - 1	-0,078	0,067					-0,099	0,033	***
d0111 t - 1	0,23	0,081	***				0,159	0,04	***
d1000 t - 1	0,163	0,076	**				0,148	0,037	***
d1001 t - 1	0,058	0,086					0,047	0,042	
d1010 t - 1	0,109	0,085					0,145	0,041	***
d1011 t - 1	0,118	0,119					0,095	0,059	
d1100 t - 1	-0,066	0,09					-0,022	0,045	
d1101 t - 1	-0,038	0,098					0,003	0,048	
d1110 t - 1	0,14	0,059	***				0,127	0,028	***
d1111 t - 1	0,206	0,065	***				0,202	0,031	***
industry dummies	yes			yes			yes		
year dummies	yes			yes			yes		
R2-adjusted	0,772								

**Table 5a. Kodde-Palm test for complementarity and substitutability: manufacturing.<sup>a</sup>**

Combination	Product/Process	Product/Organisation	Product/e-commerce	Process/Organisation	Process/e-commerce	Organisation/e-commerce
<b>I) Complementarity</b>						
Function value	<b>1,832</b>	<b>1,420</b>	<b>12,754</b>	<b>9,278</b>	<b>5,11E-06</b>	<b>2,54E-17</b>
LB Kodde-Palm 0.10 (DF = 1)	1,642	1,642	1,642	1,642	1,642	1,642
UB Kodde-Palm 0.10 (DF = 4)	7.094	7.094	7.094	7.094	7.094	7.094
LB Kodde-Palm 0.05 (DF = 1)	2,706	2,706	2,706	2,706	2,706	2,706
UB Kodde-Palm 0.05 (DF = 4)	8.761	8.761	8.761	8.761	8.761	8.761
LB Kodde-Palm 0.025 (DF = 1)	3.841	3.841	3.841	3.841	3.841	3.841
UB Kodde-Palm 0.025 (DF = 4)	10.384	10.384	10.384	10.384	10.384	10.384
<b>II) Substitutability</b>						
Function value	<b>26,794</b>	<b>11.041</b>	<b>4.425</b>	<b>5,514</b>	<b>30,896</b>	<b>7,868</b>
LB Kodde-Palm 0.10 (DF = 1)	1,642	1,642	1,642	1,642	1,642	1,642
UB Kodde-Palm 0.10 (DF = 4)	7.094	7.094	7.094	7.094	7.094	7.094
LB Kodde-Palm 0.05 (DF = 1)	2,706	2,706	2,706	2,706	2,706	2,706
UB Kodde-Palm 0.05 (DF = 4)	8.761	8.761	8.761	8.761	8.761	8.761
LB Kodde-Palm 0.025 (DF = 1)	3.841	3.841	3.841	3.841	3.841	3.841
UB Kodde-Palm 0.025 (DF = 4)	10.384	10.384	10.384	10.384	10.384	10.384

<sup>a</sup> All test statistics are based on bootstrapped covariances. <sup>b</sup> Accept  $H_0$  if test statistic smaller than lower bound, reject if larger than upper bound. If test statistics is between the bounds, the outcome is inconclusive.

**Table 5b. Kodde-Palm test for complementarity and substitutability: services.<sup>a</sup>**

Combination	Product/Process		Product/e-commerce		Process/Process		Process/e-commerce		Organisation/Process		Organisation/e-commerce	
	Product/Process	Product/Organisation	Product/e-commerce	Process/Organisation	Process/e-commerce	Process/e-commerce	Process/e-commerce	Organisation/e-commerce	Organisation/e-commerce	Organisation/e-commerce	Organisation/e-commerce	
<b>I) Complementarity</b>												
Function value	<b>7,597</b>	<b>1,748</b>	<b>11,534</b>		<b>1,486</b>	<b>1,04E-05</b>				<b>0,727</b>		
LB Kodde-Palm 0.10 (DF = 1)	1,642	1,642	1,642		1,642	1,642				1,642		
UB Kodde-Palm 0.10 (DF = 4)	7.094	7.094	7.094		7.094	7.094				7.094		
LB Kodde-Palm 0.05 (DF = 1)	2,706	2,706	2,706		2,706	2,706				2,706		
UB Kodde-Palm 0.05 (DF = 4)	8.761	8.761	8.761		8.761	8.761				8.761		
LB Kodde-Palm 0.025 (DF = 1)	3.841	3.841	3.841		3.841	3.841				3.841		
UB Kodde-Palm 0.025 (DF = 4)	10.384	10.384	10.384		10.384	10.384				10.384		
<b>II) Substitutability</b>												
Function value	<b>1,334</b>	<b>13.351</b>	<b>0.796</b>		<b>12,113</b>	<b>46,623</b>				<b>8,270</b>		
LB Kodde-Palm 0.10 (DF = 1)	1,642	1,642	1,642		1,642	1,642				1,642		
UB Kodde-Palm 0.10 (DF = 4)	7.094	7.094	7.094		7.094	7.094				7.094		
LB Kodde-Palm 0.05 (DF = 1)	2,706	2,706	2,706		2,706	2,706				2,706		
UB Kodde-Palm 0.05 (DF = 4)	8.761	8.761	8.761		8.761	8.761				8.761		
LB Kodde-Palm 0.025 (DF = 1)	3.841	3.841	3.841		3.841	3.841				3.841		
UB Kodde-Palm 0.025 (DF = 4)	10.384	10.384	10.384		10.384	10.384				10.384		

<sup>a</sup> All test statistics are based on bootstrapped covariances. <sup>b</sup> Accept  $H_0$  if test statistic smaller than lower bound, reject if larger than upper bound. If test statistics is between the bounds, the outcome is inconclusive.