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PRODUCTIVITY EFFECTS OF INNOVATION MODES: WORK IN PROGRESS

CONCEPT DISCUSSION PAPER

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Summary: Many empirical studies have confirmed the positive impact of innovation on productivity at the firm level. The focus is usually on product innovation, the main reason being that this type of innovation is the only one for which a quantitative output measure is readily available. However, there are various other types of innovation, e.g. process innovation, organisational innovation and other types of non-technological innovation. In addition, it can be argued that a firm investing in a new ICT based technology is innovative. To investigate the effect of different types of innovations on productivity, we propose a model with two innovation input equations (R&D and ICT) that feed into a knowledge production function consisting of a system of three innovation output equations (product innovation, process innovation and organisational innovation), which ultimately feeds into a productivity equation.

Keywords: innovation, ICT, productivity, CIS

Project number: *BSV-209544*
BPA number: *-BSV*
Date: *4 maart 2009*

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The views expressed in this paper are those of the authors and do not necessarily reflect any policy by Statistics Netherlands. We thank Jacques Mairesse for helpful suggestions and making available the programming code of Robin and Mairesse (2008). We thank participants at the NESTI meeting (28 October 2008) and Don Brunker for helpful suggestions. Errors are our own.

1. Introduction

In the pioneering work by Griliches (1979), the production function is augmented with R&D to account for the fact that knowledge, and the generation thereof, contributes to the output of a firm. Crépon, Duguet, and Mairesse (CDM, 1998) extended this insight to a distinction between innovation input (e.g. R&D) and innovation output (i.e. knowledge). The idea is that innovation input (research effort, and sources of knowledge) leads to the generation of knowledge, which may manifest itself in an improved product or better production methods, and is put to use in the production process.

Since the seminal contribution by CDM, many studies have confirmed the positive impact of innovation on productivity at the firm level. Examples of such studies include Lööf and Heshmati (2002) and Van Leeuwen and Klomp (2006). As in CDM, the focus in these studies is on product innovation, the main reason being that this type of innovation is the only one for which a quantitative output measure is readily available (e.g. the share of innovative products in sales from innovation surveys, or patent data). However, as recognized in current innovation surveys, there are various types of innovation, e.g. process innovation, organisational innovation and other types of non-technological innovation. In addition, it can be argued that a firm investing in a new information and communication based technology (ICT) is innovative. There is evidence that the use of ICT has a positive effect on both the innovativity and productivity of a firm (Van Leeuwen, 2008).

In this paper, we extend the CDM framework to include different types of innovation and ICT. This is one of the first studies to include three types of innovation as well as modelling ICT as an enabler of innovation. The plan is as follows. In section 2, we briefly review some related literature that has incorporated process innovation in addition to product innovation into the CDM model, and some recent work on how ICT affects innovation and productivity. In section 3 we outline our model and estimation strategy. In section 4 we describe the data and the main variables, whereas in section 5 we present the estimation results. Section 6 concludes and gives directions for further research.

2. Literature review

The CDM model has been estimated on firm data originating from innovation surveys in OECD and non-OECD countries. The models differ by the types of innovation that are considered, the modelling of their interactions, the use of quantitative or qualitative innovation indicators, and the econometric methods used to account for simultaneity and selectivity. In this brief survey, we shall focus on two generalizations of the original CDM model, the introduction of process innovations besides product innovations, and the introduction of ICT indicators. The former are readily available in the innovation surveys, the latter requires merging with data from ICT surveys.

Given that productivity gains are related to production efficiency and factor saving, it can be argued that an analysis of the productivity effects of innovation that focuses exclusively on product innovation is too restrictive. However, due to the lack of continuous output measures it is not straightforward to extend the model to other types of innovation. For product innovations most of the time it is the share of total sales that are due to innovative products that is used to measure the intensity of innovation, or alternatively the number of patents. For other types of innovation (process, organisation), it is usually only observed whether a firm has performed the innovation or not.

Griffith et al. (2006, henceforth GHMP) use the binary indicators for product and process innovation in the augmented production function as measures for innovation output in a study for four countries: France, Germany, Spain, and the UK. They estimate the corresponding knowledge production function, linking innovation inputs to innovation outputs, by two separate probits, calculate the propensities for both types of innovation, and replace them *in lieu* of the product and process dummies in the augmented production function. This controls for the possible endogeneity of innovation output. Robin and Mairesse (2008, henceforth RM) for France adjust the GHMP model slightly by estimating the knowledge production function as a bivariate probit, which allows to calculate the propensity of performing both a product and a process innovation together in addition to the probabilities of performing them separately. This term can be used to assess the possible complementarity between the two types of innovation. For manufacturing, GHMP only find a positive significant effect for process innovation in France; in the other countries it is insignificant. Product innovation, on the other hand, has a positive significant effect in all countries but Germany. For France, RM find positive effects for product and process innovation separately, and also for their combined occurrence. Their findings hold for both the manufacturing and the services sector.

Roper et al. (2008) use binary indicators for product and process innovation, as well as a mix of a continuous measure for product innovation and a binary decision variable for process innovation. Based on the Irish Innovation Panel (IIP), they find no significant effect of both types on productivity when using the binary specification. They find a significant negative effect for product innovation when using the continuous measure of innovation success (since their productivity measure is value added per employee, and capital intensity is controlled for, their result may be viewed as a total factor productivity - TFP - effect). This is interpreted as a possible disruption effect. The authors do not control for potential endogeneity, because they argue that ‘the recursive nature of the innovation value chain suggests that innovation output measures are necessarily predetermined’ (*op. cit.* p. 964). Mairesse, Mohnen and Kremp (2009) compare the effects on TFP of various quantitative and qualitative, product and process, innovation indicators, introducing them individually and controlling for their endogeneity by estimating the respective models by Asymptotic Least Squares. Contrary to Roper et al. (2008), they find a higher impact for process than for product innovation, and no significant impact only when innovation output is not controlled for its endogeneity irrespective of whether innovation is measured by qualitative or quantitative indicators.

The German innovation survey is the only exception we are aware of that includes a quantitative measure of process innovation, namely the percentage of cost reduction due to innovation. Using this data, Peters (2008) estimates the knowledge production function as two separate type-II tobit models (according to the terminology of Amemiya, 1984), and uses the predictions for product and process innovation output in the augmented production function. She finds a positive effect for product innovation, but only weak evidence for a positive impact of process innovation. Other studies using specifications with product and process innovation are Criscuolo and Haskel (2003) and Parisi et al. (2006). Criscuolo and Haskel (2003) find a (weak) positive effect of production innovation only when it is new to market; process innovation has a negative effect when it is novel, otherwise it has no effect. Parisi et al. (2006) find a positive effect for process innovation and not for product innovation. From this overview, it appears that there is at least some degree of heterogeneity in the findings about the importance and direction of both types of innovation.

With respect to the role of ICT, our work is closely related to that of the Eurostat ICT impacts project (see Eurostat, 2008). Because data on ICT investment are not available in the survey on ICT use, this international micro-data study proposes 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. The study reveals that – on average – ICT usage is positively related to firm performance. The strength of these results varies over countries, however, and it also appears that the benefits of different types of ICT usage are industry specific. Broadband use seems to be associated with a capital deepening effect (that is, the use of broadband is indicative of a larger stock of ICT capital), whereas electronic sales shows a true efficiency effect. Van Leeuwen (2008, Chapter 12 of the Eurostat report) incorporates the broadband and e-commerce variables into the standard CDM model (with innovation output represented by innovative sales per employee). It is shown 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. As regards ICT, the model used in this paper can be seen as a modification and extension of the model in Van Leeuwen (2008).

In this paper, we shall examine R&D and ICT as alternative inputs to innovation and consider the simultaneous adoption of three types of innovation output (product, process and organisational innovation). We control for the selection of firms with positive innovation inputs and the endogeneity of innovation inputs and innovation outputs in the productivity equations. To achieve this, we match data from four sources: the Community Innovation Survey (CIS) data, data on ICT use collected in the E-commerce survey (ICT), Investment Statistics (IS), and performance data calculated from the Structural Business Statistics (PS). R&D and ICT may have different impacts on innovation modes in different branches. For this reason, we will also examine the importance of the three innovation modes for manufacturing and services industry separately.

3. Model

The modelling approach follows GHMP and RM, who use an augmented CDM model to incorporate product as well as process innovation. We extend their model to include an equation for ICT as an enabler of innovation and organizational innovation as an indicator of innovation output. Quantitative as well as qualitative data are used to model innovation inputs, whereas only qualitative information is used for innovation outputs. We measure productivity as labour productivity controlling for the capital/labour ratio, the remaining terms explaining total factor productivity.

3.1 Innovation inputs: R&D and ICT

We distinguish two types of innovation inputs: R&D expenditures and ICT investment. We measure R&D investments by the total of intramural and extramural R&D expenditures. This variable is subject to selectivity, however. The question is only asked to firms with a completed/ongoing/abandoned, product and/or process, innovation, whereas other firms can also perform R&D. In addition, the variable may be censored because R&D performers may not always report R&D (e.g. when it is performed by workers in an informal way). Furthermore, only continuous R&D performers that stated to have positive R&D expenditures are used in the estimation.

In analogy to R&D, we use the investment in ICT as a measure for ICT input. There are many periods in which firms do not report investment in ICT, so in fact ICT investment is also a censored variable. Again, firms that do not report investment may in fact still have positive ICT input, e.g. through own-account development which is not recorded as investment.

For both indicators, we therefore have a certain number of zero values and missing observations. To model this pattern of zero/missing and positive observations, we use a tobit type II model, see Amemiya (1984). For R&D we have a dichotomous variable d_R that takes value 1 when R&D is observed and 0 otherwise. We associate to d_R a latent variable d_R^* such that

(1) $d_R = 1$ when $d_R^* = \alpha_1' w_{1t} + \eta_{1t} > 0$ and

$d_R = 0$ otherwise.

Likewise for ICT we have a dichotomous variable d_{ICT} to which we associate a latent variable d_{ICT}^* such that

(2) $d_{ICT} = 1$ when $d_{ICT}^* = \alpha_2' w_{2t} + \eta_{2t} > 0$ and

$d_{ICT} = 0$ otherwise.

The amount of R&D, measured by (the log of) R&D expenditures per employee, and denoted by r_t is related to another latent variable r_t^* such that

(3) $r_t = r_t^* = \beta_1' x_{1t} + \varepsilon_{1t}$ when $d_R = 1$ and zero otherwise.

Likewise, the amount of ICT, measured by (the log of) ICT investment per employee, and denoted by ICT_t is related to a latent variable ICT_t^* such that

(4) $ICT_t = ICT_t^* = \beta_2' w_{2t} + \varepsilon_{2t}$ when $d_{ICT} = 1$ and zero otherwise.

We drop the firm subscript to avoid notational clutter. For year t, w_{jt} and ,x_{jt} (j = {1,2}) are vectors of exogenous explanatory variables some of which may be common to both vectors. Each pair of random disturbances η_{1t} and ε_{1t}, and η_{2t} and ε_{2t}, is jointly iid normally distributed.

The specification for the R&D selection equation is similar to that of RM. For reasons of symmetry we use the same explanatory variables in (1) and (2). The only exception is that we assume that the intensity of broadband use can only affect the probability of being selected as an ICT investor. Besides dummy variables for industry and size, we used the following common variables in the two selection equations: a dummy variable for being part of an enterprise group, and a dummy variable referring to the dependence on foreign markets. To model the amount of R&D and ICT, we again use the same specification as applied for R&D by RM, except for the appropriability conditions for which, unlike RM, we have no observations in the Dutch innovation surveys.

Equations (1) and (3) and (2) and (4) are estimated by maximum likelihood. From these estimations, we calculate the unconditional predictions for the latent R&D and ICT investments, which feed into the innovation output equations. As in GHMP, the predictions are also calculated for the firms with zero investments.[1] Thus, by assumption, all firms have a certain amount of (unobserved) research effort and/or ICT investment.

3.2 Innovation output: product, process and organisation

Innovation input leads to innovation output, also known as ‘knowledge production’. In this study, we consider three types of innovation, namely product, process and organisational innovations. The three innovation equations are given by

(5a) $pdt_t^* = \beta_3' x_{3t} + \varepsilon_{3t}$

(5b) $pcs_t^* = \beta_4' x_{4t} + \varepsilon_{4t}$

(5c) $org_t^* = \beta_5' x_{5t} + \varepsilon_{5t}$

[1] When predicting R&D and ICT we assume that there is no cooperation and no source of funding for non-innovators, i.e. we set these variables at zero for these firms.

where x_3 to x_5 include the (unconditional) predictions of the innovation input variables from the primary equations (3) and (4). As with innovation input, the levels of generated knowledge are latent. In this case, we only observe whether a firm had a certain type of innovation or not.[2] If *pdt*, *pcs* and *org* are the corresponding dummy variables to these events, we have

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\begin{aligned}
\Pr[pdt_t = 1] \quad &= \Pr[pdt_t^* > 0] \\
&= \Pr[\beta_3' x_{3t} + \varepsilon_{3t} > 0] \\
&= \Pr[\varepsilon_{3t} < \beta_3' x_{3t}], \\
\Pr[pcs_t = 1] \quad &= \Pr[\varepsilon_{4t} < \beta_4' x_{4t}], \\
\Pr[org_t = 1] \quad &= \Pr[\varepsilon_{5t} < \beta_5' x_{5t}].
\end{aligned}
$$

We assume that ε_{3t}, ε_{4t}, and ε_{5t} follow a multivariate normal distribution. Then the three-equation system is estimated by simulated maximum likelihood using the GHK simulator (see Train, 2003). Besides reflecting the assumption that also firms that do not report investment have a certain amount of research effort or ICT investment, the advantage of using predictions for innovation input is that we are able to use the whole sample. This means that the number of observations is increased and selectivity bias is circumvented. In addition, at least if all explanatory variables in the R&D and ICT equations are exogenous, endogeneity of the innovation inputs is controlled for. Following GHMP and RM, we construct propensities for each possible combination of innovation type, and include these as proxies for knowledge in the augmented production function. Standard errors of the estimates are computed by bootstrapping. Following van Leeuwen (2008), we also include broadband intensity and e-commerce variable in the knowledge equation, to capture the application and degree sophistication of ICT.

3.3 Production function

Finally, we estimate an augmented production function to determine the semi-elasticities of productivity with respect to dichotomous innovation output measures. The equation is

$$(6) \qquad PROD_t = \beta_6' x_{6t} + \varepsilon_{6t}\,,$$

where $PROD_t$ is the (log of the) productivity of a firm, and x_6 includes the predicted innovation output measures. We use a labour productivity specification with value added per full-time equivalent employee (fte) on the left-hand side, controlling for capital and firm size on the right-hand side.

[2] For product innovation, we actually observe the percentage of total sales due to innovative products. To treat the three types of innovation in the same manner, however, we also restrict product innovation to a binary variable.

Table 1a. Summary statistics, 2002-2006

	CIS		CIS ∩ IS		CIS ∩ ICT		CIS ∩ ICT ∩ IS	
	mean	*N*	mean	*N*	mean	*N*	mean	*N*
Belonging to a group (%)	0.55	31241	0.58	24844	0.61	9479	0.66	6435
Main market: international (%)	0.34	31241	0.36	24844	0.34	9479	0.39	6435
Cooperation for innovation (%)	0.14	31241	0.15	24844	0.19	9479	0.21	6435
Local funding for innovation (%)	0.02	31241	0.02	24844	0.02	9479	0.02	6435
National funding for innovation (%)	0.08	31241	0.09	24844	0.11	9479	0.13	6435
EU funding for innovation (%)	0.02	31241	0.02	24844	0.02	9479	0.03	6435
Having access to broadband (%)	0.44	9177	0.43	7897	0.44	9177	0.44	6197
Doing e-purchases (%)	0.05	8760	0.05	7527	0.05	8760	0.05	5887
Doing e-sales (%)	0.05	9051	0.05	8140	0.05	9051	0.05	6435
R&D expenditures per fte (1000s)	4.35	10091	3.80	8386	4.88	3666	4.33	2722
ICT investment per fte (1000s)	0.71	24814	0.71	24814	0.67	8166	0.64	6129
Employment (CIS, fte)	164.27	30905	169.56	24725	249.05	9271	270.25	6421
Employment (PS, fte)	151.10	18822	158.29	17275	224.38	6435	224.38	6435
Value added per fte (1000s)	69.31	18822	69.02	17275	71.69	6435	71.69	6435

CIS: Community Innovation Survey, ICT: E-commerce Survey, IS: Investment Statistics, PS: Production Statistics.

Table 1b. Distribution of combinations of innovation types, 2002-2006

Product	Process	Organisation	N[a]	N[b]	R&D[c]	ICT[c]	Value added[c]
no	no	no	0.59	0.49	2.069[d]	0.473	75.869
no	no	yes	0.14	0.14	2.997[d]	0.647	81.070
no	yes	no	0.02	0.02	2.766	0.653	76.827
no	yes	yes	0.02	0.02	0.562	0.454	62.939
yes	no	no	0.07	0.08	4.341	0.848	69.244
yes	no	yes	0.06	0.07	4.048	0.705	71.324
yes	yes	no	0.04	0.06	5.981	0.905	66.795
yes	yes	yes	0.07	0.11	7.022	1.313	72.671

[a] Percentage of CIS sample; number of observations is 31,236.
[b] Production function sample (CIS ∩ ICT ∩ PS, number of observations is 5285).
[c] In 1000s of euro per (full-time) employee.
[d] Note: R&D expenditures are only observed for the firms with ongoing/abandoned product or process innovation projects in these groups (211 firms with no innovations, 134 with only an organisational innovation).

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 (SIC 15 to 37) as well as the services sector (SIC 50 to 93).[3] The innovation variables are sourced from the Community Innovation Survey (CIS). We pool the 2002, 2004, and 2006 editions (also referred to as respectively CIS 3.5, CIS 4 and CIS 4.5). Information on ICT use comes from the Business ICT (E-commerce) survey. Investment in ICT is taken from the Investment Statistics (IS). Finally, production data (production value, factor costs) are taken from the Production 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 levels of the standard industrial classification (SBI).[4]

Table 1a gives the summary statistics for the variables used in the model, for the different samples used in different equations. The R&D equation only uses CIS data; the ICT equation uses IS and CIS; the knowledge production function uses CIS and ICT data; finally, the TFP equation uses PS, CIS and ICT (the latter two only via the

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[3] We exclude SIC 73, the commercial R&D sector.

[4] The assumption that firms within the same industry are subject to the same price development is not trivial though. Besides the usual critique that firms are heterogeneous even at very low levels of aggregation, it is in this context not unlikely that on the output-side innovators show a different pricing behaviour from non-innovators. For example, new products may initially be more expensive due to high production costs (e.g. LCD TV’s). In addition, firms may benefit from a certain monopoly position when product innovations have not yet been imitated, whereas a large part of the production costs may also go into marketing the new product.

predicted propensities). The overall impression from table 1a is that the means of the variables are pretty much in line in the various samples. Based on the employment variables, however, it looks like 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. The tendency towards larger firms seems to go hand in hand with a slight decrease of the ICT intensity, but there is no pattern in the intensity of R&D or value added per employee.

Table 1b shows the distribution of possible combinations of innovation types. Almost 60% of the firms do not innovate at all in the sense that they do not have any of the innovation types aforementioned (this category does include somewhat over 200 firms with an ongoing or abandoned innovation project, however). Most of the innovators perform a single innovation type, of which in turn most perform an organisational innovation. Strikingly, the group that performs all three types appears relatively large compared to the innovators that have two types. In addition, we see that the group performing all three types becomes relatively more important in the estimation sample of the productivity equation.

R&D expenditures and ICT investment are higher for combinations involving product innovation, and are roughly increasing in the number of types. Both R&D and ICT investment are the highest for the group that perform all three types of innovation. The means of these variables are largely determined by a few very large observations, however. Finally, in terms of value added per employee, firms with only an organisational innovation have the highest productivity. From these figures, however, a clear relation between productivity and a specific type of innovation or the number of innovations cannot be deduced.

5. Results

In this section, the estimation results of the augmented CDM model are presented. Since one may expect that the importance of innovation modes can differ between industries, we estimated the model separately for manufacturing and services.[5]

5.1 Innovation input

Table 2a presents the estimation results for the R&D – (1) and (3) – and ICT – (2) and (4) – equations. All variables are significant without many differences in the results by sector, the only exception being some of the dummies for financial sup-

[5] 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. The effects of the variables of interest cannot be allowed to be different for subindustries, however, due to diminishing numbers of observations at lower levels of aggregation.

port. EU funding is insignificant in the ICT equations, and national funding only marginally significant. Local funding does not seem to play a role for both the R&D and ICT decisions. The finding that financial support is more important for R&D than for ICT can be understood by the fact that ICT is an instance of a General Purpose Technology that can be easily bought, and its acquisition does not have to be aimed primarily at innovation activities.

The positive sign of the indicator for being part of a group could reflect that those firms may benefit from better internal access to finance or knowledge, or other synergies that facilitate the possibility to perform R&D or to invest in ICT. However, in manufacturing being part of a group has a negative effect on selection in the case of ICT. This can be an indication that manufacturing firms that are part of a group centralize ICT services into a single business unit, or that these services are being outsourced. In this case, being part of a group reduces the possibility of positive ICT investment for a single business unit in manufacturing. We also find that firms are likely to spend more on R&D and ICT when cooperating on innovation activities. Finally, the positive sign of the indicator for foreign activities reflects that competing in a foreign market requires firms to be innovative and makes the availability of communication possibilities more vital.[6,7]

5.2 Innovation output

Results for the knowledge production function are reported in table 2b. The indicators for knowledge are just the binary variables indicating whether a firm had a particular type of innovation in a certain year. The three-equation system is estimated as a trivariate probit, accounting for the mutual dependence of the error terms.[8] Predictions for R&D and ICT investment from the pertinent equations are used as explanatory variables here, to account for possible endogeneity. In addition, since the predictions are the unconditional expectations from equation (2) and (4), these are also used for firms having missing or zero values for these variables, reflecting that those

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[6] Vice versa, innovative firms may be more likely to enter into foreign markets, receive funding, et cetera, so that one should be careful with drawing conclusions about causality. This also raises the issue of whether the indicators could be endogenous to R&D and/or ICT. We do not pursue this possibility here however, so by assumption, the variables are considered to be exogenous.

[7] In line with van Leeuwen (2008), we experimented with the percentage of broadband enable workers in the selection equation for ICT. This variable turns out to be highly significant. However, its inclusion requires linking to the E-commerce survey and reduces strongly the number of observations. In addition, the correlation between the disturbance of the selection and the primary equation (ρ) becomes significantly negative in this case, where a positive sign is expected. Therefore, we choose not to report the results of this specification here. They are available upon request.

[8] The estimation routine is adopted from Terracol (2002).

firms may well have innovation input. The use of predicted variables makes the usual standard errors invalid, however. Therefore, we also report standard errors obtained via bootstrapping the model and base the judgement about significance on these. We find that for the predicted variables in the knowledge production equation, the bootstrap standard errors are substantially larger than the usual standard errors. For the other controls this is not the case.

In line with most of the CDM literature, we find that R&D contributes positively to product innovation in manufacturing. By contrast, it is unimportant for product innovation in services, and also for the other innovation types in both sectors. Thus, R&D appears to be mainly devoted to developing new and improving existing products, but we find no evidence that this spills over to other innovation types.

On the other hand, 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. However, the broadband intensity of a firm seems to make more difference. Broadband access allows firms to quickly 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. In our results it positively affects product as well as organisational innovation in manufacturing, and all types of innovation in services.

As in Eurostat (2008), the e-commerce variables are seen as indicators for how a firm actually uses its ICT infrastructure. The percentage of e-sales shows how well a newly developed good or service can be put into the market. E-purchases show to what extent the production process on the input side has been automatized. Both electronic sales and purchases seem to matter for process innovation in both sectors. This suggests that making use of electronic channels to sell or buy products, also stimulates the innovation of how the firm’s products are made. Only in the services sector does it also stimulate the other types of innovation. The positive effect of e-sales on product innovation found in van Leeuwen (2008) can therefore be understood from the dominance of the service sector. The fact that access to broadband is significant in most cases, even in the presence of the e-commerce variables, indicates that the importance of broadband goes beyond its use in e-commerce.

These results confirm recent findings that ICT is an important enabler of capturing and processing knowledge in the innovation throughput stage. In addition, the industry differences demonstrate that ICT in general, and relatively new ICT applications (such as broadband connectivity and e-commerce) in particular, are more important in services than in manufacturing. Although broadband connectivity enhances innovation in both industries, e-commerce applications seem to be especially important in service innovation.

5.3 Production

Finally, the estimates for the production function are reported in table 3c. We use value added per employee, controlling for capital intensity using data from the PS, so that estimated effects can be interpreted as TFP effects. Two sets of results are presented. Firstly, in the left-hand panel for both sectors, the results are given for the model as discussed above where the knowledge production function consists of a trivariate probit. Secondly, to be able to focus on the contribution of organisational innovation to the equation, we also present the results of a model with only product and process innovation in the spirit of RM.

Starting with the results for the model with three types of innovation, we see that capital intensity (proxied by depreciation per fte) is positive and significant for both sectors. The coefficient on labour, which measures the deviation from constant returns to scale in this specification,[9] is insignificant for manufacturing but significantly negative for services. This indicates substantial decreasing returns to scale in this sector. This can be explained by a typical feature of services. This industry consists of many small firms operating on suboptimal scales. Kox et al. (2007) show that scale economies in services are very local and that productivity in services across size classes is hump-shaped with increasing economies of scale for small firms and decreasing economies of scale for large firms. Although we control in our model for size related selectivity, it cannot be circumvented that the linking of various data sources leads to the under representation of small firms, especially in services. Thus, having relatively more large firms in the matched samples may explain the negative estimate for the returns to scale parameter in services.

The combinations of innovations that contribute significantly to a higher productivity all involve organisational innovation. It is striking that combinations with product and process innovation do not have a positive effect on productivity when performed in isolation or jointly, but do have a positive effect when combined with an organisational innovation. This finding is consistent with the idea of possible complementarities between the different kinds of innovation, in particular that technological innovations should be backed with an organisational innovation to improve firm performance. However, the evidence for this is tentative, since there is no information in the data on whether innovations are carried out as complements or as individual projects.

From these results, it appears that is mainly organisational innovation that increases productivity. In the light of the literature on the effects of product and process innovation (see section 2), we find that the latter types of innovation increase productivity only when accompanied by an organisational innovation. The omission of non-technological innovation in existing studies is therefore a possible explanation for the varying results with respect to the effect of different types of innovation on productivity. To reinforce this point, we re-estimated the model excluding organisational innovation, specifying the knowledge production equation as a bivariate pro-

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[9] That the coefficient on employment is the deviation from constant return to scale (CRS) can be seen as follows. Starting with the Cobb-Douglas function for value added we have, $VA = A{\cdot}K^{\alpha}L^{\beta}$, and our specification is a rewritten of this, i.e. $VA/L = A(K/L)^{\alpha}L^{\alpha+\beta-1}$. Thus, CRS ($\alpha + \beta = 1$) would imply the coefficient on labour to be zero in our specification.

bit.[10] The results for both sectors are also reported in table 2c. In this specification, product and process innovation have a significant positive effect when performed jointly in manufacturing, and when performed in isolation for the services sector. With our results for the specification including organisational innovation it is possible to qualify these findings. In manufacturing, for example, we see that the combination of product and process innovation is *not* significant, unless it is combined with an organisational innovation. Moreover, in services, the insignificance of performing both a product and a process innovation, arises because when they are not combined with organisational innovation, the contemporaneous effect turns out negative (see the sign of TP(1,1,0)). When coupled with the latter, there is a positive effect, but apparently these effects cancel when omitting the organisational innovation from the model. Similarly, for services, process innovation is significant in the two innovation types model, only because its combination with organisational turns out positive. Without it, the effect is insignificant. The positive effect of product innovation in services for the two innovation types model is a bit puzzling though. In the three type model, both the sole performance of a product innovation, as well as its combination with organisational innovation is insignificant. Possibly, the parameter suffers from omitted variables bias, but further investigation is needed to explain this result.

All in all, our results say that product and process innovations do not have a positive effect without organisational innovation. The significance of each of the combinations does not vary much between the sectors. The magnitude of the estimated effects does differ, however, with stronger effects found in services.

[10] Using the `biprobit` routine in Stata.

Table 2a. Estimation results by industry for the R&D and ICT equations.

		manufacturing				services			
		R&D (N = 8536)		ICT (N = 7474)		R&D (N = 18375)		ICT (N = 14299)	
		coeff	se	coeff	se	coeff	se	coeff	se
Intensity	Belonging to a group	0.260***	0.066	0.124***	0.045	0.263***	0.100	0.148***	0.033
	Active on foreign market	0.574***	0.093	0.206***	0.056	0.974***	0.168	0.384***	0.037
	Cooperation[a]	0.432***	0.051	0.228***	0.044	0.247***	0.073	0.479***	0.046
	Local funding[a]	0.049	0.094	-0.038	0.088	0.132	0.158	0.030	0.128
	National funding[a]	0.424***	0.056	0.090*	0.047	0.685***	0.084	0.139*	0.074
	EU funding[a]	0.597***	0.105	0.103	0.104	0.533***	0.170	0.162	0.156
Selection	Belonging to a group	0.136***	0.035	-0.123***	0.033	0.177***	0.029	0.063***	0.023
	Active on foreign market	0.463***	0.034	0.183***	0.032	0.512***	0.030	0.351***	0.025
	N	2578		4660		1676		8831	
	regression error variance (σ)	1.436		1.237		1.981		1.430	
	ρ	0.639***		0.316		0.748***		0.241***	

[a] For innovation.

Dependent variables: Log of R&D expenditures per employee (R&D) and log of ICT investment per full-time employee (ICT). Selection variable: dummy for continuous R&D and positive R&D expenditures (R&D) and positive ICT investment (ICT). Estimation method is ML (type-II tobit). All equations also include size, industry and time dummies not reported. Standard errors are robust. Significance levels: *** = 1%, ** = 5%, * = 10%.

Table 2b. Estimation results by industry for the knowledge production function.

Manufacturing (N = 2574)	Product innovation			Process innovation			Organisational innovation		
	coeff	se	se (bootstrap)	coeff	se	se (bootstrap)	coeff	se	se (bootstrap)
R&D[a]	1.044**	0.247	0.435	0.618	0.234	0.400	-0.037	0.223	0.291
ICT[a]	1.039	0.654	1.262	1.415	0.622	1.204	1.540*	0.606	0.872
access to broadband	0.277**	0.096	0.125	-0.033	0.098	0.083	0.388***	0.093	0.073
Doing e-purchases	0.106	0.283	0.357	0.458*	0.267	0.270	0.255	0.272	0.309
Doing e-sales	0.140	0.180	0.200	0.442***	0.171	0.128	-0.053	0.170	0.162
ρ_{12}	0.578***								
ρ_{13}	0.254***								
ρ_{23}	0.314***								

Services (N = 4913)	Product innovation			Process innovation			Organisational innovation		
	coeff	se	se (bootstrap)	coeff	se	se (bootstrap)	coeff	se	se (bootstrap)
R&D[a]	-0.831	0.088	0.977	-0.672	0.091	0.831	-0.496	0.085	0.524
ICT[a]	3.295***	0.158	0.897	2.645***	0.167	0.747	1.832***	0.159	0.506
access to broadband	0.441***	0.051	0.070	0.195**	0.059	0.079	0.325*	0.050	0.077
Doing e-purchases	0.395***	0.125	0.080	0.164*	0.144	0.096	0.269*	0.118	0.150
Doing e-sales	0.329**	0.139	0.133	0.161*	0.149	0.097	0.191	0.133	0.158
ρ_{12}	0.510***								
ρ_{13}	0.255***								
ρ_{23}	0.260***								

[a] Predicted investment in 1000 of euros per fte (logs).

Dependent variables: dummies for product, process and organisational innovation. Estimation method: trivariate probit. All equations also include size, industry and year dummies that are not reported. Standard errors are not corrected for the fact that predicted values are used. Correlations between the errors of the pertinent equations are denoted by ρ_{ij} ($i,j \in$ {1 = product; 2 = process; 3 = organisational}). Significance levels: *** = 1%, ** = 5%, * = 10%, based on bootstrapped standard errors.

Table 2c. Estimation results by industry for the augmented production function.

innovation types	manufacturing (N = 1992) product, process, organisational			manufacturing product, process			services (N = 3319) product, process, organisational			services product, process		
	coeff	se	se (btstr)	coeff	se	se (btstr)	coeff	se	se (btstr)	coeff	se	se (btstr)
Capital intensity	0.207***	0.017	0.013	0.207***	0.017	0.016	0.250***	0.012	0.011	0.261***	0.013	0.014
Employment	-0.013	0.022	0.018	0.038**	0.017	0.017	-0.233***	0.020	0.014	-0.131***	0.017	0.025
TP(0,0,1)	1.654***	0.421	0.491				4.345***	0.472	0.571			
TP(0,1,0)	-0.905	0.766	1.100				-2.703	1.217	1.943			
TP(0,1,1)	0.984*	0.818	0.537				17.114***	2.304	2.213			
TP(1,0,0)	0.468	0.473	0.300				0.808	0.969	1.275			
TP(1,0,1)	-0.015	0.548	0.455				-0.804	0.548	0.705			
TP(1,1,0)	-0.130	0.357	0.400				-8.327***	1.328	1.262			
TP(1,1,1)	0.891***	0.199	0.193				3.932***	0.420	0.459			
BP(0,1)				0.095	0.421	0.485				7.252***	1.574	2.357
BP(1,0)				-0.079	0.172	0.160				0.917***	0.194	0.312
BP(1,1)				0.202***	0.075	0.068				-0.033	0.163	0.285
	R^2	0.31		R^2	0.30		R^2	0.36		R^2	0.31	

All specifications include industry and time dummies. BP denotes the cluster variables of the Bivariate Probit model. Estimation method is OLS. The combinations (0/1,0/1) reflect whether a firm has product and/or process innovation (0 = no, 1 = yes). TP refers to the combinations of the Trivariate Probit model: the combinations (0/1, 0/1, 0/1) reflect whether a firm has a product, process or organisational innovation. Dependent variable is log value added per fte. Capital intensity (depreciation per fte) and employment are in logs. Significance levels: *** = 1%, ** = 5%, * = 10%, based on bootstrapped standard errors.

6. Conclusions and further research

In this paper, the standard CDM framework is extended to include investment in ICT and process and organisational innovation. Including ICT investment reflects the idea that it is an enabler of innovation success, and thus a determinant of innovation output. Innovation input in our model therefore consists of investment in R&D and ICT. Extending the model with process and organisational innovation reflects the idea that productivity gains are not solely achieved by product innovation, on which the literature has focused up to now. Lacking continuous measures for the output of process and organisational innovation, innovation output is measured by dichotomous variables reflecting whether a firm performed a particular type of innovation or not. Our modelling approach of the innovation output is an extension of Robin and Mairesse (2008) to a trivariate probit including organisational innovation.

We reach some interesting conclusions:

- R&D affects the output of product innovation in the manufacturing sector. We find no evidence for an effect on process and organisational innovation in this sector. In the services sector, there is no evidence for an effect of R&D on any of the innovation types. Using R&D as a measure of innovation, as encountered frequently in the literature, therefore implicitly focuses on product innovation, and is probably most appropriate in manufacturing;
- ICT is most important for innovation success in the services sector. ICT investment, the use of broadband, and doing e-commerce, positively affect all three types of innovation in this sector. For manufacturing, ICT seems less important, although broadband use positively affects product and organisational innovation, and e-commerce is positively related to process innovation.
- Organisational innovation is the only innovation type that leads to higher contemporaneous TFP levels. Product and process innovation only lead to higher TFP when performed together with an organisational innovation. This is true for both sectors, though we find stronger effects in services. This finding puts into perspective existing work on productivity effects of innovation not taking into account non-technological innovation.

There are a number of issues that deserve further research. Firstly, since we have available various waves of the CIS, 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 severely complicates the econometrics for this model.

The availability of a panel also allows 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). Finally, we also came across the technical problem of calculating the marginal effects for a multivariate probit model. This issue does not seem to have been tackled appropriately in the available literature. We plan on presenting a solution for this in a follow-up to this research.

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