Complementarities between Information Technologies and Innovation Modes in the Adoption and Outcome Stage: A Micro-Econometric Analysis for the Netherlands

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Abstract.

This paper empirically examines the existence and performance impact of complementarities between different modes of innovation on the one hand and information technology (IT) investments on the other hand. Innovation is conserved as a complementarity enforcing phenomenon. Complementarities are distinguished in two stages: adoption stage (i.e. when innovation adoption decisions are made) and outcome stage (i.e. when performance impacts of innovations are realized). Four innovation profiles are distinguished: 1) product innovations, 2) process innovations, 3) organizational innovations and 4) marketing innovations. A simultaneous equation model is used. It consists of three equations. The first one aims at estimating the impact of the innovation profiles on the productivity performance of the firm and is an augmented production function with the IT capital and innovation profiles as explanatory variables – besides labor and non-IT capital. The second equation deals with the innovation adoption decision of the firm and relates the innovation profiles as dependent variables to a number of innovation input variables like R&D intensity. The third equation is an auxiliary R&D equation to correct for sample selection bias. These equations are estimated with a multivariate probit model using instrument variables to correct for endogeneity and simultaneity problems.

The model is estimated with data of firms in the Netherlands for the period 2002-2008 originating from various (bi-)annual firm-level surveys provided by Statistics Netherlands. The results reveal statistical evidence of complementarities between different modes of innovation. In other words, a firm that innovates in one innovation mode has a higher probability to innovate in other innovation modes. Another finding is that the determinants of innovation adoption differ strongly between manufacturing and services firms. With regard to the productivity performance, the results reveal the presence of significant complementarities between IT and specific types of innovation as well as between different modes of innovation. Firms combining several innovations types and/or supplement their innovations with IT investments typically achieve a higher productivity.

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1. Introduction

Since the 1980s, many studies have focused on the impact of information technology (IT) investments on firm productivity. Brynjolfsson and Saunders (2010) argue that one of the most important gaps in the field of IT business value research is how complementary investments affect the relationship between IT and productivity. In a recent paper, Zand *et al.* (2011) empirically investigate the impact of different clusters of organizational complementarities on the productivity effects of IT. An important finding in this study is that organizational changes have important complementarities, with significant moderating effects on the relationship between IT investments and firm productivity. However, their firm-level analysis reveals that different modes of organizational change have differing moderating effects. Furthermore, it seems that the patterns of complementarities significantly differ between manufacturing and services firms.

At the macro level, information technology is considered as a General Purpose Technology (Breshanan and Trajtenberg, 1995) with two main characteristics: productivity improvement and innovation spawning (Jovanovic and Rousseau, 2005). Macro-level innovations then act as important forces leading to complementarities at the micro level.

The limited number of studies dealing with complementarities focus on the productivity stage of the firm, i.e. when value is created and observed. No attention has been paid to the importance of complementarities when investment decisions are made, i.e. at the technology adoption stage. The present study is an empirical investigation of the impact of different modes of innovation (as a complementary enforcing phenomenon) on the relationship between IT investments and firm productivity. The complementarity effects are compared between the adoption and the productivity stages of the firm. The analysis distinguishes between four innovation profiles: 1) product innovations, 2) process innovations, 3) organizational innovations, and 4) marketing innovations. It also differentiates between the manufacturing and services sector as significant differences between these can be expected (Brynjolfsson and Hitt, 2000; Zand *et.al*, 2011).

The main contribution of this paper is that it investigates through a simultaneous equation model how different innovation modes as complementarity encouraging forces affect the impact of IT investments on productivity performance of the firm. It also distinguishes between the decision and outcome stages of innovation adoption. Hereby it takes into account simultaneity and endogeneity problems that are so common in this kind of studies. The main findings, based on an analysis of firms in the Netherlands in the period 2002-2008, are threefold. First, firms that innovate in one innovation mode have a higher probability to innovate in other innovation modes; this means that synergistic effects exist between different innovation modes. Second, determinant of the innovation adoption decision differ strongly between the manufacturing and services sectors. Third, with regard to the productivity effects, the results document the presence of complementarities; firms conducting several innovation types jointly or supplementing them with IT investments typically achieve a higher productivity compared to those that do not engage in innovation activities or conduct innovations in isolation.

In the next section, a short theoretical background is presented. Section 3 discusses the empirical framework consisting of three sets of equations. In section 4, the data and the operationalization process are described. The estimations are presented and discussed in Section 5 and the final section concludes the paper and recommends promising areas for future research.

2. Theoretical Background

2.1. Innovation Modes

Innovation can take several modes depending on the nature of changes it brings to an organization. Organizational innovations consist of major changes in the structure of the firm (e.g. due to a reorganization or a new management method) or its relations with external parties (e.g. outsourcing). Many of these changes are initiated or stimulated by IT. Besides organizational innovations, other modes of innovations are important as well. These constitute process, product and marketing innovations. Process innovations are of a technical character and mainly IT driven. Many changes in production methods and business processes in the last twenty years have been provoked by the capability of IT to improve communication, coordination, and efficiency. This kind of innovations is particularly relevant in the manufacturing industry and fits in the standard neoclassical framework as an outward shift of the production frontier (Solow, 1956; Romer, 1986). Product innovations affect productivity as new products better fit to the consumers' tastes and create more value for them. This is particularly relevant in the services sector, where products (i.e. mainly intangible services) can be enhanced or supplemented by digital options of IT (e.g. software, media, business and financial services). Marketing innovations consist of new packaging and design of products aimed at framing consumer tastes so that these fit better to the supplied products. Marketing innovations are closely connected to product innovations and organizational innovations relate more to process innovations.

The innovation literature in the last twenty years has extensively discussed the many ways of measuring innovation (Hagedoorn, 2003; Kleinknecht and Mohnen, 2002). The focus has been mainly on whether R&D inputs/expenditures, patents or innovative products' sales output can be considered as valid innovation indicators. Hardly any attention has been paid to different modes of innovation as output indicators, and their role as complementary practices that facilitate the impact of IT investments on productivity at the firm level (OECD, 2005).

The focus on (combinations of) different innovation output modes is important when investigating the impact of innovations as complementarities in different sectors of the economy. Generally, the manufacturing sector is more innovation-intensive than the services sector as far as the (R&D-based) technical innovations are concerned. If firms do innovate, it is quite likely that process innovation will be the most dominant type among all innovation modes in manufacturing firms while organizational innovation is expected to be the most dominant one in the services sector. If this is true and if different innovations affect the relationship between IT investments and productivity changes differently, this might explain different patterns of clustering and complementarities to be relevant in different sectors (Zand *et.al,* 2011).

2.2. IT Roles with Regard to Innovation

Information technology is considered as a general purpose technology (GPT). As a GPT, its two important characteristics are productivity improvement and innovation spawning (Breshanan and Trajtenberg, 1995; Jovanovic and Rousseau, 2005; Lipsey *et.al*, 2005: 97-98). The incentives to innovate that are generated by IT affect productivity along two lines. First, innovations in the IT sector itself are remarkable. For example, Google developed Google maps that can be used in navigation systems and location-based services (i.e. IT-based innovations). The second line– and these are of main interest in this paper– are non-IT innovations, mostly organizational innovations, which can be conducive for the firm's productivity.

IT plays multiple roles as long as the innovative capacity of the firm is considered. Overall, IT roles can be classified in two broad categories.

1. *Information component of IT*: IT leads to creation, collection, processing, and communication of more and better quality information. The newly available information can be part of a new product, for instance software. The information part also becomes important in process innovations such as a new reservation system in a travel agency, GPS tracking systems in logistics firms or when applying built-to-order production methods in manufacturing plants. Organizational innovations may rely on the information component of IT when delegation of authorities (resulting in flattening of hierarchies and organizational delayering) happens; managers need to have information about and control over their employees in a more informed way. Establishing databases of best practices is another example here. Marketing innovation can also use the informational role of IT when for example newsletters and emails are sent to customers to introduce new products or loyalty cards are introduced.

2. *Technology component of IT*: IT leads to automation and integration of firm activities that result in reduction of costs, improved quality, etc. The technology component of IT deals with those aspects of IT use that replace manual interventions without necessarily relying on new sources of information. Examples include computerization of check-in operations at airports (as an example of a service innovation). Automation of product design and development processes through CAD/CAM/CAE systems is an example of the automational role of IT in process innovations. As to organizational innovations, implementation of supply chain management systems such as automatic ordering, invoicing and billing is a relevant example. Direct sales through a company website is an example of automating marketing and sales operations of the firm through IT use.

The above decomposition of IT roles for innovation is related to the 3-stage framework of Remenyi *et.al* (1994) which identifies three general uses for IT: information, automation, and transformation. The transformation role of IT in fact manifests itself in the form of an innovation. Similarly, Mooney *et al.* (1996) distinguish between three impacts of IT on processes and practices of the firm: informational, automational, and transformational. They define the three primary effects/roles of IT as follow. Automational effects refer to the efficiency perspective of value, deriving from the role of IT as a capital asset being substituted for labor. Informational effects emerge primarily from IT's capacity to collect, store, process, and disseminate information. Transformational effects refer to the value deriving from IT's ability to facilitate and support process innovation and organizational transformation.

The intensity/strength of complementarities between different modes of innovation and IT depends on the importance and involvement of the above two components in design and implementation of any specific type of innovation. How important is the availability of new information for implementation of a specific type of innovation? How important is technology-based automation for implementing a specific type of innovation?

2.3. Adoption vs. Productivity Stage

The Innovation Diffusion Theory (IDT) explicates that organizations decide on adopting an innovation depending on, among others, its perceived usefulness and expected impact (Rogers 1995). Information technology is considered as an important innovation. On the basis of IDT, if managers and decision-makers a priori perceive or expect some sort of synergy or complementarity between specific modes of innovation (being product, process, organizational, marketing innovation), they will make decisions in favor of joint adoption of these particular modes. Therefore, IDT can predict that, ceteris paribus, the rate of adoption of different configurations or clusters of innovations will be different, depending on the intensity of complementarities among them. Yet, the managers' decisions are limited by their bounded rationality: the extent of information they have (for example, about the usefulness of different modes of innovation and their mutual synergies) and the cognitive limitations to predict the relative impact of different innovation modes and their complementarities.

While the IDT primarily focuses on the adoption stage of innovations, it gives less attention towards their (joint) outcomes and how they create business value for the firm. The bounded rationality of innovation and technology decision-makers makes this issue even more critical as innovations may result in undesirable and/or unanticipated consequences. Rogers (2003) states that this is an area which requires further research. The complementarities line of thought (Milgrom and Roberts, 1990; 1995) seems to be a very strong candidate to supplement and enhance the IDT. It has its focus on the outcome stage of innovations (as a particular type of organizational practices). The theory of complementarities conceives the dynamics of organizational transformation a more complex and contingent phenomenon, as described by Milgrom and Roberts (1995: 191): "changing only a few of the system elements at a time to their optimal values may not come at all close to achieving all the benefits that are available through a fully coordinated move, and may even have negative payoffs." This suggests that partial or piecemeal implementation of innovations might lead to worse outcomes, compared to the unchanged status quo.

The present paper is an attempt to provide insights into the rationality of decision-makers through comparing the existence and extent of complementarities in the adoption (i.e. decision) and productivity (i.e. impact) stages of innovation processes. It does that by synthesizing the innovation diffusion theory and the complementarities theory, which will provide us with a framework to analyze both the adoption as well as the productivity stages of organizational innovations.

3. Empirical Models and Methods of Analysis

The empirical framework in this paper consists of three equations. The first one is an augmented production function (Griliches, 1979, Pakes and Griliches, 1984) that relates production factors– among which IT investments and innovation modes – to labor productivity as the dependent variable. Therefore, we consider innovation to be an additional factor of production, besides traditional inputs (i.e. capital and labor). In other words, we investigate if the innovation profile of firms explains productivity differences among them. The second equation is an innovation decision equation which relates different innovation profiles to total factor productivity (TFP). We model the decisions to adopt a certain innovation profile in order to investigate the drivers/determinants of specific clusters of innovations. The separate modelling of the innovation and the productivity equations allows us to assess possible complementarities in both the adoption as well as the productivity stages. The third equation is an auxiliary R&D equation. In this equation we consider R&D investment as a measure of innovation effort, as it is an input into the development of new products and/or processes.

3.1. The Augmented Production Function

Consider the Cobb-Douglas production function given by:

$$VA_t = A_t IT_t^{\alpha_1} K_t^{\alpha_2} L_t^{\alpha_3} \Leftrightarrow \log(VA_t / L_t) = a_t + \alpha_1 it_t + \alpha_2 k_t + (\alpha_3 - 1) l_t$$

where VA_t is value added, IT_t is the stock of IT capital, K_t is the (non-IT) capital stock, and L_t is employment. The term A_t reflects differences in firm output that are not related to differences in inputs, and is usually referred to as total factor productivity (TFP). Our main interest in this paper is to investigate whether differences or changes in TFP relate to differences in the innovation profile of firms.

We distinguish between four types of innovation: (1) product innovation, (2) process innovation, (3) organizational innovation, and (4) marketing innovation. Firms face a strategic choice with respect to the adoption of any of these innovation types. The innovation profile I_t defines which of these innovations are adopted, and which are not

$$I_t = \{ y_{1t}, y_{2t}, y_{3t}, y_{4t} \},$$

where $y_{1t} = 1$ if a firm has adopted a product innovation;

$y_{2t} = 1$ if a firm has adopted a process innovation;

$y_{3t} = 1$ if a firm has adopted an organizational innovation;

$y_{4t} = 1$ if a firm has adopted a marketing innovation.

Define d_j to be a dummy indicator for each of the innovation profiles,

$$d_{jt} = 1[I_t = \{i_{1t}, i_{2t}, i_{3t}, i_{4t}\}], \quad j = 1,...,16,$$

that is,

$$d_{1t} = 1[I_t = \{0,0,0,0\}], d_{2t}[I_t = \{0,0,0,1\}], \ldots, d_{16t}[I_t = \{1,1,1,1\}].$$

To investigate whether the innovation profiles explain productivity differences, we parameterize a_t by innovation profile dummies d_{jt},

(1) $$a_t = \sum_j \gamma_j d_{jt} + \varepsilon_t .$$

Note that adopted innovations can explain productivity differences in two ways. First, a particular innovation may be more productivity enhancing than another. Thus, firms adopting this particular type of innovation may experience a higher productivity (i.e. an outward shift of technical efficiency). Second, certain innovations may also be mutually reinforcing, so that their combination leads to a higher level of productivity than when they are performed in isolation (i.e. synergistic effects).

Finally, we also investigate whether or not the innovation types and the use of IT are complementary. This is captured by the inclusion of interaction terms between innovation profiles and IT capital, i.e.

(3) $$a_t = \sum_j \gamma_j d_{jt} + \sum_k \beta_k y_{kt} it_t + \varepsilon_t .$$

For the estimation, IT capital is proxied by the number of workers who make frequent use of a computer at their workplace (variable *pc* in Table 1 below). Non-IT capital is proxied by depreciation costs. This considerably increases the number of observations to be used in the production function estimation compared to using (IT and non-IT) capital stock estimates obtained from a Perpetual Inventory Method. An alternative would be to estimate missing capital stock values with a Heckman procedure, using the number of computer users and depreciation costs as predictors.

To account for the endogenous nature of the innovation profile dummies, we use a two-stage approach in which the propensities for each profile is predicted using a multivariate probit model. This equation is described in section 3.2. Replacing the dummies by the predicted propensities, we estimate the augmented production function by Ordinary Least Squares (OLS).

3.2. The Innovation Adoption Decision

We explicitly model the adoption decision concerning different types of innovation. This serves several purposes. First, we are interested in the drivers of these adoption decisions. Which contextual factors or firm characteristics influence the probability of adopting a particular type of innovation? Second, the innovation profile dummies in the productivity equation in section 3.1 are endogenous. By modelling the decision stage, we are able to construct propensities for each innovation profile. These propensities can be viewed as predictions for the endogenous dummy variables. By appropriately dealing with simultaneity and endogeneity in modelling the decision stage, we can replace the endogenous dummies by the predicted propensities of innovation modes (more or less in a two-stage instrumental variable type of approach). Third, this method enables us to investigate possible complementarities in the innovation adoption stage. That is, if firms anticipate the complementary nature of two innovations (*ex ante*), we expect to see that decisions in favour of these two innovations would occur simultaneously, and they will also have mutually reinforcing effects on each other's adoption probabilities. Although the latter issue (i.e. investigating complementarities in the adoption stage) is left for the future research, we formulate our empirical models in general terms so as to incorporate the possibility of this investigation. We present some preliminary descriptive evidence on the relevance of this phenomenon in section 5.1.

Let y_{it}^* be the (latent) value of adopting innovation type i = 1,2,3,4. The value of adoption depends on a vector of explanatory variables X_{it}, and on the vector of decisions about the other three types of innovation, denoted by y_{-i},

$$y_{it}^* = X_{it}\beta_i + \alpha_i y_{-i,t} + \varepsilon_{it}, \qquad (i = 1,2,3,4).$$

We observe $y_i = 1$ if $y_{it}^* > 0$, and zero otherwise. Thus,

$$\Pr(y_i = 1) = \Pr(y_{it}^* > 0)$$

$$= \Pr(\varepsilon_{it} > -X_{it}\beta_i - \alpha_i y_{-i,t}) \quad (i = 1,2,3,4).$$

This is a system of simultaneous equations with limited dependent variables. Under the assumption of jointly normally distributed errors, it is a simultaneous multivariate (*casu quo* 'quadrivariate') probit model.

The explanatory variables we consider in each equation of the multivariate probit model may vary per equation. In particular, we consider innovation effort variables (e.g. R&D collaboration, R&D expenditure, and external funding) as an explanatory variable for technological (i.e. product and process) innovation, but not for non-technological innovation (i.e. organizational and marketing). Instead, the intensity of teleworking and sales costs are considered as extra explanatory variables for organizational and marketing innovations respectively. Variables that are common determinants of all the innovation decisions are ICT use variables (automation systems, electronic sales and electronic purchase) and the intensity of high speed (broadband) internet usage. Other control variables include dummies for foreign ownership and being part of an enterprise group, firm size, and the usual year and industry dummies. We arrive at the following vectors of explanatory variables

$$X_{1t} = \{gp_t, for\_own_t, co_t, fun, ict\_sys_t, HQ\_pct_t, esales_t, epurch_t, \log(RnD_t)\}$$

$$X_{2t} = \{gp_t, for\_own_t, co_t, fun, ict\_sys_t, HQ\_pct_t, esales_t, epurch_t, \log(RnD_t)\}$$

$$X_{3t} = \{gp_t, for\_own_t, ict\_sys_t, HQ\_pct_t, esales_t, epurch_t, telework_t)\}$$

$$X_{4t} = \{gp_t, for\_own_t, ict\_sys_t, HQ\_pct_t, esales_t, epurch_t, \log(salescosts_t)\}$$

where the variable names are explained in Table 1. Although we will focus on the complementarity issue in the decision stage in our upcoming research efforts, for the time being we do not allow for it (i.e. we set $\alpha_{i,t} = 0$).

Following Crépon et al. (1998), we see R&D investment as a measure of innovation effort which is an input into the development of new products and processes. We measure R&D investments by the sum of intramural and extramural R&D expenditures. This variable is subject to selectivity, however. In our data, only firms with a product and/or process innovation are asked to report their R&D spending (and those who are in the process of developing such an innovation, or have abandoned it at an earlier stage). Still, not all these (innovating) firms report R&D expenditure, so the observed value may equal zero. Furthermore, only continuous (and not incidental) R&D performers that have declared to have a positive R&D expenditure are used in the estimations. In line with Crépon et al. (1998) and Griffith et al. (2006), we assume that all firms, in reality, have some amount of innovation effort (although very small), even if their R&D investment is missing or zero. A reason to assume this is that R&D may not be carried out in a formal way, even though a firm's employees perform innovative efforts and/or deliver innovations. Moreover, innovative efforts can be broader than what is generally understood as R&D (for instance, the gathering of knowledge). Thus, firms that do not report R&D may have innovative efforts, and for the firms that do report R&D, this may be an underestimation of their actual innovative effort. Hence, we will generate estimates of innovative efforts for all firms using information on R&D. We do this by linking R&D investment per capita to explanatory variables. To model the pattern of zero/missing and positive observations, we need to control for sample selection in order to produce consistent estimates, which is achieved via a type II tobit model, see Amemiya (1984).[1] The appendix describes the specification of this equation in more detail.

The multivariate probit model is estimated by Simulated Maximum Likelihood using the method provided by Cappellari and Jenkins (2003). Using these results, we calculate the propensities building on the work of Cappellari and Jenkins (2006), extending their code to be able to calculate all propensities.

4. Data, Descriptives and Operationalization

4.1. The Sample

The data used in this paper is sourced from Statistics Netherlands and incudes various firm-level surveys. Information on innovation and R&D comes from the Community Innovation Survey (CIS) that is carried out in even years. IT data is obtained from the annual ICT survey. Data on production and employment is taken from the national Production Statistics (PS). Investment data is obtained through the national Investment Statistics (IS). CIS and ICT are a census for firms with more than 100 employees; for firms with less than 100 employees, the data is gathered through (independent) stratified samples. There is no data for firms with less than 10 employees. PS is a census for firms with more than 50 employees; below 50 employees, the data is collected through independent stratification. PS includes no data for firms with less than 10 employees. IS data is a census for firms with more than 20 employees. Firms with less than 20 employees form a stratified sample.[2]

The data are biannual and cover the period 2002 to 2008 (four years in total). The sample includes both the manufacturing (NACE 15-37) and services sectors (NACE 50-74) of the economy. The transport sector (NACE 60-63) is not included in the empirical analysis due to the lack of capital stock data for this sector. We drop the commercial R&D sector (NACE 73), because it is atypical in the context of this study (R&D is atypically high in this sector, and it is

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[1] This stage of the model follows the modeling of R&D in Polder et al. (2010).

[2] See http://www.cbs.nl/nl-NL/menu/themas/bedrijven/methoden/dataverzameling/ for more details on survey characteristics. Some descriptions may only be available in Dutch.

primarily carried out for commercial purposes (i.e. servicing the external parties) and not to increase the firm's own knowledge). Some observations concern extreme values for R&D intensity: those with R&D investment per employee higher than 2 million euros were excluded from analysis. PM: also dropped extreme value for salescost pe.

Nominal values of monetary variables were converted to real values using price deflators from the EU-KLEMS database for (gross output and intermediate use) and from the National Accounts (for R&D investment).

4.2. Operationalization of Variables

Table 1 explains the construction of variables used in this study.

Table 1: Operationalization of Variables

Variable	**Survey**	**Explanation**
ICT use variables		
telework	ICT	the percentage of workers having access to the firm's internal network outside the office
ict_sys	ICT	a dummy for the use of automization systems for procurement and sales orders
epurch	ICT	the percentage of electronic purchases through internet
esales	ICT	the percentage of electronic sales through internet
HQ_internet	ICT	a dummy indicating if the firm has access to high-speed internet through xdsl, wireless or other high quality connection types
intpers	ICT	the percentage of workers having access to internet
HQ_pct		intensity of the use of high quality internet = *HQ_internet* * *intpers* (see Eurostat, 2008 for further details)
pc use	ICT	number of employees using a computer/PC at their workplace; this variable is used as a proxy for the ICT capital of the firm
Innovation variables		
RnD	CIS	sum of intramural and extramural R&D investments per employee

prod_inn	CIS	a dummy for product innovation (goods and/or services)
proc_inn	CIS	a dummy for process innovation (production, logistics, or supporting activities)
org_inn	CIS	a dummy for organizational innovation (management structure or external relations)
mkt_inn	CIS	a dummy for marketing innovation (design or packaging)
gp	CIS	a dummy for being part of an enterprise group
for_own	CIS	a dummy for being part of an enterprise group with the head office outside the Netherlands
co	CIS	a dummy for cooperation with third parties on innovation activities (only observed for product and/or process innovators; zeroes are imputed for missing values)
fun	CIS	a dummy for receiving public funds for innovation activities (see the remark of *co* on how to treat missing values)
Production and employment variables		
salescosts	PS	amount of sales costs per employee (including promotion and R&D costs); monetary variables are per employee and in logs unless otherwise stated
Q	PS	gross output
L	PS	employment (if not available in PS we use the corresponding variable in CIS. N.b. this variable is used as the denominator in all 'per employee' variables)
IV	PS	intermediate use (costs of energy, materials and services)
VA	PS	value-added at factor costs (= $Q - IV$)
depreciation	PS	total depreciation costs; this variable is used as a proxy for the non-ICT capital of the firm

Table 2: Descriptive Statistics

Variable	Measurement Unit	Mean	Standard Deviation	Mean	Standard Deviation
		Manufacturing		*Services*	
group	0/1	0,748	0,434	0,636	0,481
foreign owned	0/1	0,337	0,473	0,213	0,409
R&D collaboration	0/1	0,359	0,480	0,141	0,348
innovation funding	0/1	0,300	0,458	0,055	0,229
IT-based automation systems	0/1	0,900	0,300	0,731	0,444
high quality internet intensity	%	0,320	0,284	0,471	0,414
e-purchasing	%	0,040	0,125	0,071	0,186
e-sales	%	0,031	0,114	0,039	0,131
R&D per employee	1,000 €	4,667	16,511	2,943	8,486
teleworkers	%	0,081	0,129	0,150	0,248
sales costs per employee	1,000 €	5,645	11,901	5,611	17,835
gross output per employee	1,000 €	282,10	467,70	326,01	458,25
value added per employee	1,000 €	72,14	65,32	73,88	87,91
PC use	# employees	124.27	325.61	205.75	1072
depreciation cost	1,000 €	2518.46	10875.21	2115.77	22391.27
number of employees	Fte	252,60	500,52	289,46	516,44

4.3. Descriptive Statistics

Table 2 reports the descriptive statistics of the sample. On average, services firms in our sample are larger than those in the manufacturing sector; they also exhibit a large spread. As expected, R&D collaboration, R&D expenditure, and external funding of innovation projects are more common among manufacturing than services firms. Access to high speed internet and conducting commerce/business through it (sell- or buy-side) is more dominant in the services sector. The nature of services firms also allows them to rely more heavily on teleworking practices. As to the capital stocks, services firms are more IT-intensive while manufacturing are, in general, more capital-intensive (IT capital and non-IT capital being proxied by respectively PC use and depreciation cost).

Table 3 reports the distribution of different types of innovation among the sampled firms. Table 3 shows that our (sub-)samples are biased towards larger and more innovative firms. This is due to the sampling frame of CIS survey that is primarily sent to larger organizations with higher probabilities of engaging in innovation projects. This fact shall be taken into account when interpreting and generalizing the findings and implications of this research.

Table 3: Distribution of Innovation Modes

Innovation	Population Estimate (weighted)	Estimation Sample (N=2,973)	Population Estimate (weighted)	Estimation Sample (N=4,535)
product	0,302	0,511	0,141	0,225
process	0,269	0,430	0,125	0,198
organizational	0,231	0,376	0,176	0,284
marketing	0,103	0,177	0,061	0,092
employment	84	213	53	238

Table 4 shows sectoral distribution of the samples (at NACE-2).

Table 4: Sectoral Distribution of the Samples

NACE Sector (rev. 1.1)	CIS (population)	Estimation sample
15	3,1	3,68
16	0,02	0,17
17	0,53	1,55
18	0,17	0,33
19	0,09	0,32
20	0,86	1,23
21	0,49	2,41
22	2,49	3,2
23	0,05	0,4
24	0,9	5,13
25	1,07	2,37
26	0,84	2,17
27	0,25	1,58
28	4,31	3,86
29	3,06	3,25
30	0,08	0,24
31	0,56	1,12
32	0,2	0,51
33	0,8	1,53
34	0,51	1,12
35	0,62	1,2
36	1,61	1,85
37	0,16	0,39
50	5,31	2,92
51	16,84	9,24
52	11,1	5,54
55	7,2	4,74
60	6,07	3,88
61	0,42	0,81
62	0,05	0,33
63	2,31	3,25
64	0,56	1,19
71	0,78	1,17
72	3,29	6,22
74	18,32	21,11

5. Results and Discussion

5.1. Descriptive Evidence for Complementarity of Innovation Modes in the Decision Stage

In this section we present some preliminary descriptive evidence on the interrelation between innovation decisions. Figure 1 shows the frequency distribution of the innovation profiles. Clearly, the largest category is formed by the firms that do not have any of innovation types. This is especially the case for services, where 56% of the sampled firms are not innovative in any way, against 32% for manufacturing. For the innovative subsample, the four largest categories in manufacturing all involve product innovation, which is not surprising considering the nature of output in this industry. It is striking that there are far more firms that combine product innovation with another type of innovation. In fact, the categories in which product innovation is combined with a process innovation (1,1,0,0), and with a process innovation and an organizational innovation (1,1,1,0), are individually larger than the category of firms carrying out only product innovation; the percentage of firms combining all types of innovation is approximately the same as that of firms with only product innovation. It seems that manufacturing firms that perform a product innovation are also strongly inclined to complement it with other innovation types. In services, however, the picture is less clear-cut. Three of the four largest categories involve a single innovation type in this case (product, process and organizational innovation), the fourth category being the one in which these three innovations are combined. An organizational innovation by itself is the most common among the innovating services firms. Therefore, at first sight, unlike in manufacturing, services firms innovating in one way do not seem to be inclined to innovate in other ways. This could point at. lower degrees of complementarity in the innovation adoption phase for services.

Figure 1: Frequency Distribution of Innovation Profiles

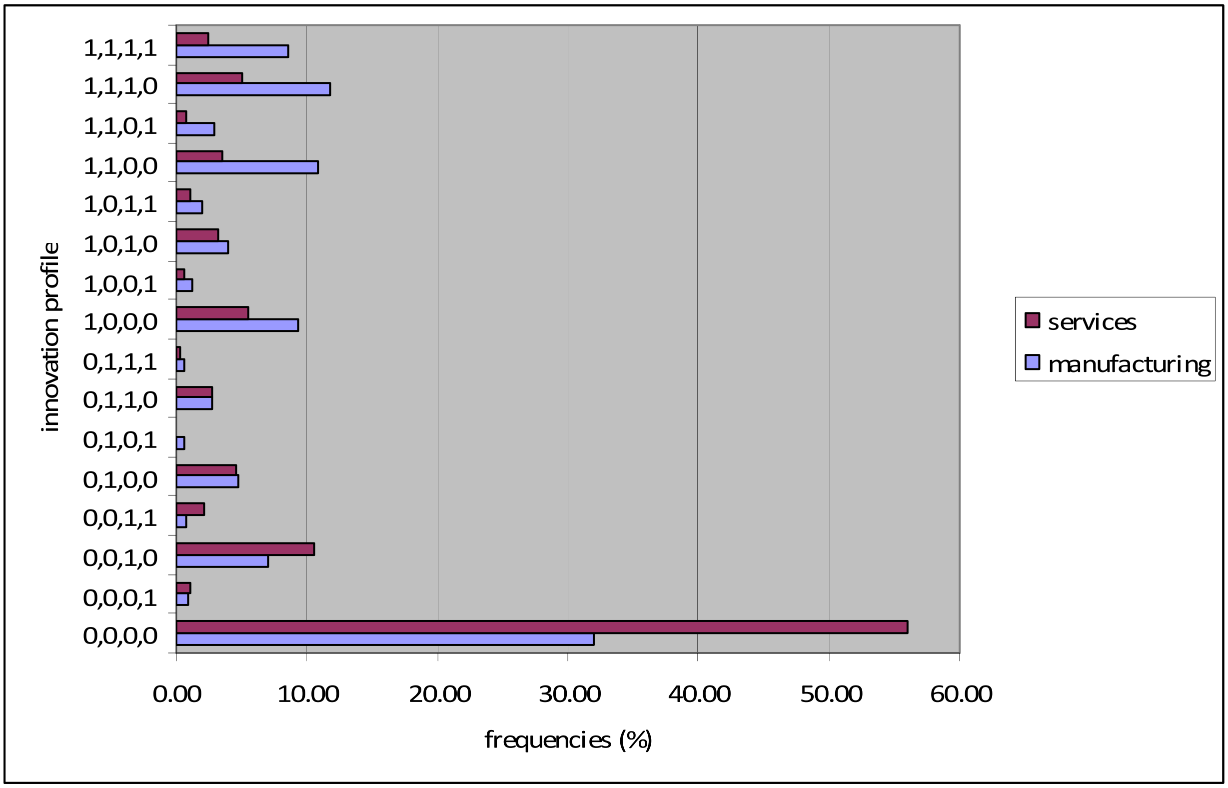

Table 5 shows the sample marginal, joint and conditional probabilities for the various types of innovation. These estimates are based on sample frequencies reported in table 3 (for example, the probability of a product innovation is simply the sum of the frequencies of all innovation profiles involving a product innovation). If the probabilities for having a particular type of innovation were independent (say that the firm tosses a coin to make the adoption decisions), the joint probability for two innovation types would be the product of the two marginal probabilities (column Pr(A)×Pr(B)). However, if we look at the sample joint probabilities Pr(A ∧ B), we see that for each combination the observed probability is substantially higher. In other words, doing one type of innovation increases the probability of doing another. This is the case in both sectors.

Table 5: Marginal, Joint, and Conditional Sample Probabilities for Innovation Types.

Manufacturing (N = 3,046)								
A	**B**	**Pr(A)**	**Pr(B)**	**Pr(A)xPr(B)**	**Pr(A & B)**	**Pr(A|B)**	**Pr(B|A)**	**Pr(A|B)/Pr(A) = Pr(B|A)/Pr(B)**
prod	proc	50.63	42.72	21.63	34.15	79.94	67.45	1.58
prod	org	50.63	37.51	18.99	26.34	70.22	52.02	1.39
prod	mkt	50.63	17.41	8.81	14.58	83.74	28.80	1.65
proc	org	42.72	37.51	16.02	23.65	63.05	55.36	1.48
proc	mkt	42.72	17.41	7.44	12.55	72.09	29.38	1.69
org	mkt	37.51	17.41	6.53	11.86	68.12	31.62	1.82
Services (N = 4,775)								
A	**B**	**Pr(A)**	**Pr(B)**	**Pr(A)xPr(B)**	**Pr(A & B)**	**Pr(A|B)**	**Pr(B|A)**	**Pr(A|B)/Pr(A) = Pr(B|A)/Pr(B)**
prod	proc	22.14	19.77	4.38	11.84	59.89	53.48	2.71
prod	org	22.14	27.76	6.15	11.83	42.62	53.43	1.92
prod	mkt	22.14	8.8	1.95	4.96	56.36	22.40	2.55
proc	org	19.77	27.76	5.49	10.71	38.58	54.17	1.95
proc	mkt	19.77	8.8	1.74	3.80	43.18	19.22	2.18
org	mkt	27.76	8.8	2.44	6.18	70.23	22.26	2.53

Another way to look at this is to compare the conditional probability (of A given B, Pr(A|B)) to the marginal probability (of A, Pr(A)).[3] From the last column in table 5, it is clear that the

[3] Note that the ratio of these two probabilities is symmetric in A and B: Pr(A|B)/Pr(A) = Pr(B|A)/Pr(B). Moreover, Pr(A|B)/Pr(A) = Pr(B|A)/Pr(B) = Pr(A)×Pr(B)/Pr(A $\wedge$ B).

probability of innovation type A increases substantially when one knows that it has performed an innovation type B. In manufacturing, especially the probability of a marketing innovation increases with the presence of other innovations. In services, the probability for each innovation type (providing the co-presence of another type of innovation) is increased relatively more than in manufacturing. Again, the probability of a marketing innovation increases more than the other probabilities, but also the increase in the probability of a product or a process innovation is relatively high, when it is given that the firm is also performing another type of innovation.

Combining the results of Figure 1 and Table 5, we see that while innovation is more common in manufacturing than in services, and combining different types of innovation is also more frequent in manufacturing, the increases in the probabilities of a particular type of innovation when it is known that the firm performs another type of innovation as well are higher in the services sector. Figure 1 and table 5 are *prima facie* evidence of possible complementarities between innovation types. If firms are rational, they have information and/or reliable expectations about the future productivity effects of different innovation types, and know that certain types of innovations are mutually reinforcing, the probability that these types are carried out simultaneously increases. Thus far, the descriptive evidence presented in Table 2 is consistent with this view. However, this type of analysis does not shed light on the underlying mechanism for how and why innovations are actually combined (Athey and Stern, 1998). In particular, certain firm characteristics or contextual factors may cause innovations to be (effectively) combined. For example, firms having an innovative or risk-taking management are more likely to be innovative in a broad sense than firms having a more conservative or risk-averse management. As a result, a more rigorous econometric analysis is needed to take these factors into account, and to be able to make statements about whether or not innovation types are combined because of their complementary nature (or alternatively, because of other reasons). The general model described in section 3.2 could be a device to answer such questions.

5.2. Estimation Results for the Innovation Adoption Stage (Multivariate Probit Model)

The results for the innovation adoption stage are presented in table 6. We explain the probability for the adoption of different types of innovation from a number of explanatory variables (discussed in section 4.2). To structure the discussion we group the variables into five categories:

1. The first set of variables relates to *inputs* into the different types of innovation: R&D is an input into technological (product and process) innovation, the extent of teleworking may be an input for the firm to change certain aspects of its structural organization (e.g. flexible workplaces), and sales costs may capture efforts of the firm in developing marketing strategies. We find that R&D is insignificant, except for process innovation in manufacturing.[4] Teleworking does not seem to be significantly related to innovation, while firms that spend more on sales costs have a higher probability of adopting a marketing innovation.

2. The second category of variables refers to the *connectivity* of the firm, i.e. how well is the firm connected to its external environment, i.e. how easy can it share or gather information? This is captured by the existence of automated systems for sales and procurement (e.g. placing and receiving of orders, automated billing, and electronic payment), and the intensity of using a high quality internet connection. We find that connectivity is very strongly positively related to all types of innovation. Having an automated system for sales and/or procurement increases the probability of any kind of innovation. The intensity of using a high quality internet connection also increases the probability of each type of innovation, except that of process innovation in the manufacturing sector.

[4] R&D is predicted from a type-II Tobit model as described in the appendix. Results for this equation are available upon request.

Table 6: Estimation results innovation adoption equation (multivariate probit).

Manufacturing	**product**			**process**			**organizational**			**marketing**		
(*N* = 2973)	coeff		se	coeff		se	coeff		se	coeff		se
R&D per employee	0.728		1.950	5.474	***	1.868						
teleworkers							0.144		0.214			
salescost per employee										0.118	***	0.022
high quality internet intensity	0.369	***	0.115	-0.153		0.107	0.496	***	0.110	0.293	**	0.117
e-purchasing	0.025		0.237	-0.087		0.217	0.635	***	0.207	0.517	**	0.230
e-sales	-0.082		0.253	0.498	**	0.235	-0.380		0.221	0.061		0.240
group	-0.042		0.207	-0.474		0.198	0.192	***	0.065	0.100		0.076
foreignly owned	-0.128		0.128	-0.310		0.122	-0.042		0.059	-0.003		0.068
automization system	0.427	***	0.098	0.215	**	0.093	0.295	***	0.091	0.200	*	0.113
collaboration for innovation	0.686		0.839	-1.532		0.802						
funding for innovation	0.640		0.742	-1.584		0.709						
Log-likelihood	-5775.03											

continued on next page

Table 6. (continued)

Services	**product**			**process**			**organizational**			**marketing**		
(*N* = 4575)	coeff		se	coeff		se	coeff		se	coeff		se
R&D per employee	-0.135		0.102	-0.233		0.104						
teleworkers							0.100		0.089			
salescost per employee										0.100	***	0.020
high quality internet intensity	0.556	***	0.066	0.209	***	0.066	0.425	***	0.061	0.360	***	0.077
e-purchasing	0.448	***	0.127	0.206		0.126	0.262	**	0.112	0.258	*	0.141
e-sales	0.122		0.177	0.102		0.178	0.164		0.153	0.010		0.200
group	0.072		0.063	0.010		0.062	0.134	***	0.049	0.031		0.065
foreignly owned	0.182	**	0.077	-0.009		0.077	0.083		0.053	0.059		0.070
automization system	0.101	*	0.060	0.194	***	0.061	0.281	***	0.052	0.209	***	0.072
collaboration for innovation	1.400	***	0.088	1.349	***	0.087						
funding for innovation	1.146	***	0.127	0.634	***	0.119						
Log-likelihood	-6809.28											

*** = significance at 0.01; ** = significance at 0.05; * = significance at 0.10.

Dependent variables: dummies for product, process, organizational and marketing innovation. The estimation follows the Simulated Maximum Likelihood procedure by Cappellari and Jenkins (2003), using 50 draws. Industry, size, and year dummies are included but not reported. Standard errors are not corrected for the use of predicted R&D.

3. The third category is formed by the extent of *e-commerce* in the firm (e-purchasing and e-selling). These variables can also be thought to capture how advanced the IT use of a firm is (Eurostat, 2008). E-purchasing positively affects non-technological innovation in both sectors. It also positively affects product innovation in services. E-sales does not seem to contribute to a higher probability of any type of innovation, except in the case of process innovation in manufacturing. Overall, e-commerce – as an indicator of advanced IT use – has a positive effect on innovation in both sectors.

4. The fourth category contains the group and foreign ownership dummies, indicating that the firm is part of a larger *enterprise*. These variables may capture different aspects which influence innovativeness: access to knowledge (information within the affiliates of the enterprise group and/or, in case of foreign ownership, other countries), and access to (internal) finance. Moreover, from an organizational perspective, being part of an enterprise group increases the need for coordination, the more the locations are spread over various locations. We find that these variables seem to be less important when we control for the IT use of the firm. However, what is striking is that in both manufacturing and services, being part of an enterprise group increases the probability of an organizational innovation. This could indeed reflect that the value of organizational changes aimed at improving coordination among the various units increases once an enterprise comprises more business units (especially, when scattered geographically). Foreign ownership, on the other hand, only seems to positively affect product innovation in services. This could reflect the introduction of services provided in the home country by the owning company in another location (through an affiliate);

5. Finally, the fifth category relates to additional variables *stimulating technological innovation*, such as collaboration on innovation with other firms, and external funding. We find that these variables do not make a difference in manufacturing. However, both the probability of product and process innovations are positively affected by these variables for services firms. Knowing from Table 2 that funding and cooperation are

relatively rare in services, receiving funding or cooperating with other firms appears more effective (in explaining innovation activities of firms) in this sector.

5.3. Estimation Results for the Productivity Stage (Augmented Production Function)

We now turn to the productivity stage. Table 7 shows the estimation results for the augmented production function. In this equation, IT capital and non-IT capital are separated, and proxied by respectively the number of PC users and depreciation costs. We also include an employment term to allow for non-constant returns to scale. To account for the possible endogeneity of the innovation profile dummies, we replaced them by the predicted propensities obtained from the results of the multivariate probit equation discussed in section 5.2. Finally, to investigate possible complementarities between IT capital and innovation, we interact dummies for each type of innovation with the IT capital proxy (note that the innovation dummies refer to individual innovation types, not to the innovation profiles that refer to sets of innovation types adopted by the firm). These dummies are replaced by the corresponding predicted marginal probabilities to account for endogeneity. The coefficients on the interaction terms can be interpreted as corrections to the estimated elasticity on IT capital, given that a firm has performed a particular innovation, and indicate complementarities between IT and innovation modes.

Non-IT capital and employment are significant in both sectors. The coefficient on employment points at significant decreasing returns to scale, especially in services. Moreover, IT capital by itself is insignificant in both sectors. Nevertheless, in manufacturing, its interaction with product innovation is negative, and with marketing innovation is positive. Thus, the elasticity on IT capital becomes positive and significant when marketing innovation is involved, or in other words, IT and marketing innovation complement each other. The negative sign on the interaction between IT capital and product innovation could point at possible substitutability between the two. In services, IT capital and process innovation are complements, and also IT capital and organizational innovation. The interaction with product innovation has a negative effect, as in manufacturing, and also the interaction with marketing innovation is negative, suggesting possible substitutability.

Table 7: Estimation results production function (OLS)

	Manufacturing (N = 2836)		**Services (N = 4304)**	
	coeff.	se.	coeff.	se.
IT capital	-0.004	0.005	-0.005	0.005
non-IT capital	0.202 ***	0.012	0.211 ***	0.010
employment	-0.202 ***	0.023	-0.373 ***	0.019
innovation profiles				
0,0,0,1	5.084 **	2.261	2.194	1.417
0,0,1,0	2.312	1.885	2.754 **	1.293
0,0,1,1	0.560	1.102	3.005 ***	0.603
0,1,0,0	3.236	1.844	3.232 **	1.333
0,1,0,1	-1.278	1.152	4.341 ***	1.561
0,1,1,0	-0.397	0.797	-2.549 ***	0.526
0,1,1,1	4.425 **	2.035	3.399 **	1.576
1,0,0,0	1.311	1.517	1.215	1.475
1,0,0,1	1.754	2.337	8.072 ***	2.844
1,0,1,0	1.609	1.430	0.180	1.177
1,0,1,1	3.701 *	2.109	1.686	2.311
1,1,0,0	0.627	0.972	0.785	0.617
1,1,0,1	5.563 ***	1.367	6.008 ***	2.088
1,1,1,0	2.632 **	1.172	1.213	1.156
1,1,1,1	0.168	0.956	4.623 ***	1.255
IT × product	-0.054 **	0.024	-0.117 ***	0.036
IT × process	0.039	0.024	0.112 **	0.044
IT × organizational	-0.023	0.026	0.259 ***	0.046
IT × marketing	0.148 ***	0.039	-0.286 ***	0.089
R^2	0.35		0.38	

*** = significance at 0.01; ** = significance at 0.05; * = significance at 0.10.

Dependent variables: log value added per employee. Industry and year dummies are included but not reported. Standard errors are not corrected for the use of predicted propensities for innovation profiles.

Turning to the innovation profile dummies, we see that, overall, innovation has a more distinctive effect on productivity in services, where more of the dummies are significant than in manufacturing. All coefficients are relative to base category where a firm has not adopted any of the innovation types. In manufacturing, the combinations including marketing innovation have a significantly higher productivity than the base category. Moreover, apart from marketing innovation alone, all other significant dummies involve three types of innovation. Thus, firms combining several types of innovation achieve a higher productivity, which is a clear sign of complementarity (although the combination of all four types of innovation is not significant). Also in services, we find evidence for synergies among innovation modes. For example, product and marketing innovations are not significant by themselves, but their combination has a significantly positive effect on productivity. Moreover, most other combinations involving either product or marketing innovation increase productivity as well. An exception is the combination of process and organizational innovation, which has a negative effect, although both of these types of innovation have a positive effect when adopted in isolation.

Although the results are suggestive for complementarities between different types of innovation, to make better statements about complementarity (and possibly substitutability) it is necessary to test this in a formal way, see e.g. Carree et al. (2010) and Polder et al. (2010). At this point, this is left for future research and extended versions of the present paper.

6. Conclusions and Future Research Directions

The main conclusion of this paper is that we do find empirical evidence for the complementary role of innovations as an enforcing phenomenon on the relationship between information technology investments and productivity of the firm, for firms in both the manufacturing and services sectors in the Netherlands. Four innovation profiles are distinguished in this research: 1) product innovations, 2) process innovations, 3) organizational innovations and 4) marketing innovations. The main conclusion is built up from the following sub-conclusions.

First, a simple probability analysis revealed statistical evidence of complementarities between different innovation modes at the adoption stage. In other words, a firm that innovates in one innovation mode has a higher probability to be active in other innovation modes as well. Second, a more thorough investigation of the determinants of these complementarities shows 1) that determinants strongly differ between manufacturing and services firms, and 2) that technical facilities aimed at high connectivity to customers and suppliers are an important determinant of the innovation adoption decision for nearly all four innovation modes considered in this study. Collaboration on innovation with external partners seems to affect the probability to innovate in any of the four innovation modes positively in the services sector but not in the manufacturing sector. Finally, estimating the impact of the innovation modes on the productivity performance of the firm- defined as the natural logarithm of value added per employee- shows that firms combining several types of innovations achieve a higher productivity. This clearly suggests the presence of complementarities between the different innovation modes. Output elasticity of IT capital is surprisingly insignificant in contrast to labor and non-IT capital in both manufacturing and services sectors. The complementarities between IT capital and product innovation are significantly negative in both manufacturing and services sectors. Complementarities between IT capital and marketing innovation are significantly positive in the manufacturing sector and significantly negative in the services sector. Complementarities between IT, on the one hand, and process or organizational innovation, on the other hand, is significantly positive in services but nonexistent in manufacturing firms. The complementarities between different innovation modes are strongly present for the services sector but much less for the manufacturing sector. Possible substitutability seems to be a likely explanation for the negative interactions between the IT capital and innovation activities of the firm.

Our results are preliminary and the authors plan to do follow-up research in four fronts. First, it is necessary to investigate more thoroughly the existence and intensity of complementarities at the innovation adoption stage. We expect to find that firms that adopt a certain innovation (e.g. product innovation) will also show a higher probability to adopt other innovations (such as process or marketing innovations). Second, it is necessary to test more formally for the complementarity and substitutability relationships between different types of innovation in order to come to stronger conclusions. The framework of Kodde and Palm (1986) seem to be a proper approach for doing this. Third, we aim to further look at specific mechanisms that may lead to negative interactions between IT and innovation modes (in contrast to the general belief that IT and innovation are always complementarity). We also intend to look at sector-specific differences that result in diverging effects and complementarity patterns in the manufacturing and services sectors of the economy. Finally, providing that we can get access to comparable data (in terms of details and representativeness) for other countries, we want to conduct cross-country analyses that would reveal whether or not our findings are specific to the Netherlands or can be more safely generalized.

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Appendix: The R&D Input Equation

Following Crépon et al. (1998), we see R&D investment as a measure of innovation effort which is an input into the development of new products and processes. We measure R&D investments by the sum of intramural and extramural R&D expenditures. This variable is subject to selectivity, however. In our data, only firms with a product and/or process innovation are asked to report their R&D spending (and those who are in the process of developing such an innovation, or have abandoned it at an earlier stage). Still, not all these (innovating) firms report R&D expenditure, so the observed value may equal zero. Furthermore, only continuous (and not incidental) R&D performers that have declared to have a positive R&D expenditure are used in the estimations. In line with Crépon et al. (1998) and Griffith et al. (2006), we assume that all firms, in reality, have some amount of innovation effort (although very small), even if their R&D investment is missing or zero. A reason to assume this is that R&D may not be carried out in a formal way, even though a firm's employees perform innovative efforts and/or deliver innovations. Moreover, innovative efforts can be broader than what is generally understood as R&D (for instance, the gathering of knowledge). Thus, firms that do not report R&D may have innovative efforts, and for the firms that do report R&D, this may be an underestimation of their actual innovative effort.

Hence, we will generate estimates of innovative efforts for all firms using information on R&D. We do this by linking R&D investment per capita to explanatory variables. Because R&D may be missing or equal to zero, we need to control for sample selection in order to produce consistent estimates. To model the pattern of zero/missing and positive observations, we use a type II tobit model, see Amemiya (1984).[5] Let d_R be a dichotomous variable that takes value 1 when a firm is a continuous R&D performer, and 0 otherwise. We associate to d_R a latent variable d_R^* such that

$d_R = 1$ when $d_{R,t}^* = W_t \beta_W + \eta_t > 0$ and

$d_R = 0$ otherwise.

[5] This stage of the model follows the modeling of R&D in Polder et al. (2010).

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

$$r_t = r_t^* = Z_t \beta_Z + \omega_t \text{ when } d_R = 1 \text{ and zero otherwise.}$$

For year t, W_t and Z_t are vectors of exogenous explanatory variables some of which may be common to both vectors. The random disturbances η_t and ω_t are assumed to be jointly iid normally distributed. Besides dummy variables for time, industry and size, we include in W_t a dummy variable for being part of an enterprise group, and a dummy variable referring to the dependence of the firm on foreign markets (as a proxy for international competition). To model the amount of R&D, we include in Z_t the variables in W_t and add a dummy for cooperation in innovative activities and dummies for funding from local, national, or European Union sources.