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Abstract

This paper investigates the importance of the educational mix of employees at the firm level for the probability of firms being involved in innovation activities. We distinguish between four types of innovation: product, process, organisational, and marketing innovation. Moreover, we consider three different types of education for employees with at least 16 years of schooling: technical sciences, social sciences, and humanities. Furthermore, we examine the influence of these different innovation activities on firm productivity. Using a rotating panel data sample of Danish firms, we find that different types of innovations are related to distinct educational types. Moreover, we find that firms that adopt product and marketing innovation are more productive than firms that adopt product innovation but not marketing innovation and firms that adopt marketing innovation but not product innovation. In addition, firms that adopt organisational and process innovation demonstrate greated productivity levels than forms that adopt organisational innovation but not process innovation that again demonstrate greater productivity than firms that do not adopt process innovation but not organisational innovation. Finally, we establish that product and marketing innovation as well as organisational and process innovation are complementary inputs using formal tests for supermodularity. Complementarity can be rejected for all other pairs of innovation types.

Keywords: Educational composition, human capital, innovation, productivity, complementarity.
JEL classification: J24, D24, O31, O32

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1. Introduction

The main idea of this paper is that educated employees play a key role in innovation activities and that innovation leads to higher productivity. Our perspective is that firms that intensively use educated labourers will be more active in innovation practices compared with firms that do not employ this type of employee intensively. A large number of studies motivates this idea: industry- and firm-level studies (e.g., Jorgenson (1995) and McMorrow et al. (2009)) show the positive relationships among research and development (R&D) investments, educational level (measured by number of years of schooling), and total factor productivity (TFP) growth, whereas other studies (e.g., Kiiski and Pohjola (2002), Chinn and Fairlie (2007), and Brynjolfsson and Saunders (2010)) find that firms with a higher number of educated workers are more likely to adopt new technology and innovative systems. Furthermore, Uzawa (1965), Romer (1990), Barro (1997), and Aghion and Howitt (1998) provide macroeconomic models in which human capital can enhance the probability of innovation and emphasise the importance of employees working in R&D areas. In addition, Jones (1995) motivates his semi-endogenous growth model by measuring the number of engineers in R&D as an input in knowledge production, and Romer (2001) argues that engineers and natural scientists are relevant for R&D. Finally, Sørensen (1999) and Funke and Strulik (2000) both study the relationship between human capital accumulation, R&D and productivity growth.

The productive effects of a broad set of innovation types, including technical and non-technical aspects, are examined in the present paper. Four innovation types are included, and in addition to product and process innovation, we include changes in firm organisational and marketing activities. Therefore, the analysis is consistent with the broad definition of innovation in the Oslo Manual: "An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations" (OECD (2005), p. 46).

The literature on innovation has primarily focused on the technological aspects of innovation, such as product and process innovation, investments in information and communication technology (ICT), and R&D investments (Hall (2011)). During the past decade, non-technical aspects of innovation have been found to be important for firm performance in empirical studies: Lazear (2000) emphasises the important role of human resource management in the efficiency of firms; Caroli and Van Reenen (2001) study the important interaction between organisational changes and skills for enhancing TFP, and Bloom and Van Reenen (2007 and 2011) find that productive firms are associated with better management practices. Furthermore, Bloom and Van Reenen (2010) argue that basic business education can improve the management and organisation of firms and thus emphasise the important role of skills in innovation.

Empirical studies of the productive effects of marketing are scarce in the economic literature. In the literature on business administration, the importance of marketing is sometimes suggested to be a relevant complementary factor for product innovation. It might not be sufficient for a firm to improve existing products or introduce new products without strong coordination and the ability to commercialise these products. In the marketing literature, Gupta et al. (1986) suggest that the integration of R&D investments with marketing policies can influence success in R&D, whereas Dutta et al. (1999) find that the interaction between marketing and R&D capabilities is correlated with firm performance as measured by Tobin's q. As a matter of example, Park (2004) finds that the standardisation of the VHS format for the video cassette recorder market at the expense of Betamax can be explained by the reliability of the brand and the marketing ability, that enhanced the network diffusion of the product.

Motivated by the abovementioned studies of the integration of R&D and marketing, we formulate a hypothesis regarding the complementarity between marketing and product innovation. In this relationship, we must emphasise that product innovation is a significantly broader concept than R&D and that we do not restrict the analysis to a narrowly defined high-tech industry.[1] Our hypothesis states that firms that adopt product and marketing innovation have higher productivity levels than firms that adopt either product or marketing innovation. The suggested mechanism is that product innovation generates new products and product improvements that potentially shift the firm demand curve outward, whereas marketing innovation informs existing and new markets about the new and improved products of a firm. For product innovation to be successful in terms of higher demand, marketing innovation is important in generating a complementary effect.

To the best of our knowledge, this paper presents the first attempt that includes organisational and marketing innovation in addition to process and product innovation. Consequently, this study is also the first empirical analysis in the economic literature of the productive effects of adopting a combination of product and marketing innovations. Polder et al. (2010) investigate product, process, and organisational innovation but do not include marketing innovation and thus are unable to focus on effects of complementarity between product and marketing innovation.

The applied model is a modified version of the three-stage framework introduced by Crepon et al. (1998), where our application is based on two stages. In the first stage, a knowledge production function that is based on the probabilities of adopting different types of innovation is estimated, whereas a production function that is augmented with innovation activities is estimated in the second stage. More precisely, the predicted perceived probabilities of innovation that are developed in the first stage are included in the estimation of the production function along with other background variables. In addition to estimating the knowledge production function and the production function for goods and services, we perform tests to identify complementarity among the different innovation types.

[1] The Oslo Manual states as: "A product innovation is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, incorporated software, user friendliness or other functional characteristics", OECD (2005). According to the Frascati manual, R&D activities are defined as "[engagement] in basic and applied research to acquire new knowledge", "direct research towards specific inventions or modifications of existing techniques", and "[development of] new product and process concepts or other new methods" OECD (2002).

The key explanatory variables in the estimation of the knowledge production function in the first stage are variables that measure the education mix of the firms in the sample. We do not target specific departments of firms when focusing on the relationship between the education mix and the probabilities of adopting different innovation types (i.e., we do not restrict the analysis to employees in R&D or other specific departments of firms). Rather, we hypothesise that a more intensive use of educated labourers increases the probabilities of being active in different innovation types and that these activities can be performed in any part of a firm. The education mix at the firm level can be measured using a unique link between the Danish version of the community innovation surveys (CIS) and a Danish employer-employee matched data set that includes detailed educational information pertaining to individual employees that can be tracked to the firm level.

Educated labourers can also be employed in the production of goods and services in addition to serving as an input in knowledge creation. As a consequence, we treat educated labourers as input both in the production of goods and services and in the production of knowledge. The share of employees with more than 16 years of schooling is incorporated as input in knowledge production and is further divided into three types of education: technical sciences, social sciences, and humanities. In addition, the shares of employees who have completed different amounts of education are treated as inputs in the production of goods and services. In this respect we distinguish between unskilled and skilled workers as well as 14, 16, and 18 or more years of schooling. In other words, the share of employees with 16 years or more of education is treated differently for knowledge production than for the production of goods and services. For knowledge production, the share is subdivided after educational type, whereas the share is subdivided after educational length for the production of goods and services. In this sense, we consider that the education mix can influence the production of goods and services through a direct channel and through an indirect channel (knowledge production), which is innovation in this case.

The second stage of the estimation procedure is based on a Cobb-Douglas production function that is augmented with innovation activities that are measured by the predicted perceived probabilities of innovation types. From an empirical perspective, disentangling the different types of innovation is challenging because most innovation types coexist in the production function and thus create possible problems of collinearities (Anderson and Schmittlein (1984), Milgrom and Roberts (1990) and Athey and Stern (1998)). For this reason a number of probabilities for combinations of innovation types are determined and included in the estimation of the production function. In the analysis we limit complementarity to exist between product and marketing innovation as well as organisational innovation. The motivation for this is discussed in the theoretical section. In addition, we test for the supermodularity of the production function, which provides information regarding the complementarity among innovation types. In this respect, we provide empirical support for included the two interaction terms between 4 innovation types only.

Four main results are established. First, firms are often involved in more than one innovation type. It is interesting that relatively many firms perform product and marketing innovation as well as organisational and process innovation. Moreover, many firms do either product innovation but not marketing innovation; marketing innovation but not product innovation; organisational innovation but not process innovation; or process innovation but not organisational innovation. In other words, the data set permits us to perform the empirical analysis since we are able to distinguish different firm types.

Second, the educational structure is important for the types of innovation that are adopted by firms. We find that the intensive use of employees with more than 16 years of schooling increases the probability of adopting innovation. Different types of education increase the probability of adopting different types of innovation. This result suggests that education types other than technical education are important for knowledge production. More precisely, the probability for product innovation increases with the share of employees educated in humanities, social sciences, and technical sciences; the probability for process innovation increases with the share of employees educated in technical sciences; the probability for organisational innovation especially increases with the share of employees educated in the technical sciences and social sciences; and the probability for marketing innovation especially increases with the share of employees educated in social sciences and humanities.

Third, firms that adopt product and marketing innovation are more productive than firms that adopt product innovation but not marketing innovation and firms that adopt marketing innovation but not product innovation. In this sense, product and marketing innovation are complementary innovation types. Moreover, the estimates suggest that firms that perform organisational and process innovation have higher productivity that firms that perform organisational innovation but no process innovation that again have higher productivity levels than firms with process innovation but no organisational innovation. The latter firm type has similar productivity levels as firms without innovation. The result that firms that adopt organisational innovation as the only innovation type have higher productivity levels than firms that do not adopt this type of innovation echoes the findings of Caroli and Van Reenen (2001) who find that organisational changes have an independent role in productivity growth.

Fourth, complementarity between different innovation types is investigated using a formal test for supermodularity, and the hypotheses of the complementarity between product and marketing innovation as well as between organisational and process innovation cannot be rejected. Complementarity between all other pairs of innovation types can be rejected, except between product and process innovation for which the test is inconclusive.

A final note on the applied methodology should be mentioned. Hall et al. (2012) build a model that is similar to our model but use R&D intensities and ICT investments as key variables for predicting the innovation probabilities rather than variables that reflect the education mix of the firms. We do not include R&D intensities even though the variable exists for the applied sample of firms because this variable does not play a role when variables that measure the education mix are introduced; when the education mix is excluded from the first stage, the R&D intensity enters positive and significantly in explaining the probabilities of innovation, whereas it enters insignificantly when the education mix is included. Moreover, we do not include ICT measures, as we do not have access to this measure in the Danish CIS surveys. This variable is available in other survey data for Danish firms based on different samples and will reduce the sample size significantly when merged with the survey data on innovation. Therefore, we do not include this variable.

The remainder of the paper is structured as follows: Section 2 introduces a short theoretical framework that studies the interactions between the different types of education, innovation and productivity. Section 3 introduces the empirical framework. Section 4 describes the data. Section 5 presents the results complementarities between innovation types are tested. Section 6 concludes the paper. The concept and test of supermodularity of the production function is described in an appendix.

2. Theoretical Framework

We assume that firm i's production function at time t is defined by an extended version of the Cobb-Douglas production function:

$$q_{it} = a_{it} + \alpha k_{it} + \beta l_{it} + \gamma I_{1,it} \tag{1}$$

where q is the quantity produced, a is the log of TFP, k is the level of capital and l is the labour input. Lower case letters refer to log values. Furthermore, we assume that the production function is extended by innovation activities relevant for production as measured by I_1. Subscripts i and t refer to firm and year, respectively.

Following Griliches and Mairesse (1984) and Hall (2011), we decompose the natural logarithm of the real revenue r of firm i at time t as

$$r_{it} = \pi_{it} + q_{it} \tag{2}$$

where π is the nominal value added price that is deflated by the industry price index. Furthermore, we define the iso-elastic demand equation as function of price π and of innovation relevant for demand I_2:

$$q_{it} = \eta \pi_{it} + \phi I_{2,it} \tag{3}$$

where the $\eta < 0$ denotes the demand elasticities.

Combining (1) and (2), we obtain the specification form that motivates the equation that is applied in the empirical analysis:

$$r_{it} = \left(\frac{\eta + 1}{\eta}\right)(a_{it} + \alpha k_{it} + \beta l_{it}) + \gamma \left(\frac{\eta + 1}{\eta}\right) I_{1,it} - \frac{\phi}{\eta} I_{2,it} \tag{4}$$

I_2 has a positive effect on r since $\phi > 0$ and $\eta < 0$. I_1 has a positive effect on r for $-1 > \eta$, whereas the relationship between innovation relevant for production and real value added is negative when $-1 < \eta < 0$. This relationship is clarified by Hall (2011), whose work the above model setup follows.

Innovation relevant for production affects real value added through I_1 that is a function of the intensities of innovation in process, $I^{*,c}$ and in organisation, $I^{*,o}$. Real value added is also affected by innovation relevant for demand, I_2, that is a function of the intensities of innovation in product, $I^{*,p}$ and in marketing $I^{*,m}$. This implies that

$$\begin{aligned} I_1 &= I_1\left(I_{it}^{*,c}, I_{it}^{*,o}\right) \\ I_2 &= I_2\left(I_{it}^{*,p}, I_{it}^{*,m}\right) \end{aligned}$$

The functions $I_1(.,.)$ and $I_2(.,.)$ are assumed to satisfy the following conditions:

$$\frac{\partial I_1(.,.)}{\partial I^{*,c}} > 0, \frac{\partial I_1(.,.)}{\partial I^{*,o}} > 0, \frac{\partial I_2(.,.)}{\partial I^{*,p}} > 0, \frac{\partial I_2(.,.)}{\partial I^{*,m}} > 0$$

Moreover, the different innovation types relevant for production and demand, respectively, are assumed to influence the effects of one another, and this influence implies that innovation types may be complementary inputs. Specifically, we hypothesise that firms that adopt product and marketing innovation have higher levels of productivity than firms that adopt only product or marketing innovation. The motivation for this hypothesis is that these two types of innovation are important for firm demand. Product innovation generates new products and product improvements that potentially shift the demand curve outward. Marketing innovation informs existing and new markets about the products of a firm. For product innovation to be successful in terms of higher demand, marketing innovation is an important input. This implies the following:

$$\frac{\partial I_1(.,.)}{\partial I^{*,p}\partial I^{*,m}} > 0 \tag{5}$$

In addition, we hypothesise that firms that adopt process and organisational innovation have higher productivity levels than firms that adopt only process innovation or organisational innovation. The motivation for this hypothesis is that these two types of innovation are important for production efficiency, i.e., the innovation types are important for (1). Process innovation generates improved or new production methods, distribution and logistics systems, or support functions. Successful implementation often also requires organisational innovation (e.g., see Bresnahan et al. (2002) and Bartel et al. (2007)). This implies that:

$$\frac{\partial I_2(.,.)}{\partial I^{*,c}\partial I^{*,o}} > 0 \tag{6}$$

3. Empirical Framework

In this section, we outline the empirical framework and discuss a number of issues related to the applied estimation methods. Specifically, we focus on the implementation of the innovation functions $I_1 = I_1\left(I_{it}^{*,c}, I_{it}^{*,o}\right)$ and $I_2 = I_2\left(I_{it}^{*,p}, I_{it}^{*,m}\right)$. An asterisk indicates that the variable is a latent variable. Our empirical framework is a modified version of the econometric model that is described by Crepon et al. (1998), Griffith et al. (2006), and Polder et al. (2010) and is based on a two stage estimation procedure: innovation equations and a productivity equation.

3.1. The Innovation Equation

The knowledge production function is described by a set of two separate two-equation probability response models for simultaneous innovation activities:

$$\begin{cases} I_{it}^{*,p} = \delta_1 Z_{it} + \epsilon_{1,it} \\ I_{it}^{*,m} = \delta_2 Z_{it} + \epsilon_{2,it} \end{cases} \tag{7}$$

and

$$\begin{cases} I_{it}^{*,c} = \delta_3 Z_{it} + \epsilon_{3,it} \\ I_{it}^{*,o} = \delta_4 Z_{it} + \epsilon_{4,it} \end{cases} \tag{8}$$

where Z_{it} is a set of explanatory variables that are common for all four innovation equations, and this set of variables is described in the next section. Moreover, $E\left[\epsilon_1\right] = E\left[\epsilon_2\right] = E\left[\epsilon_3\right] = E\left[\epsilon_4\right] = 0$, $Var\left[\epsilon_1\right] = Var\left[\epsilon_2\right] = Var\left[\epsilon_3\right] = Var\left[\epsilon_4\right] = 1$ and $Cov\left(\epsilon_1, \epsilon_2\right) = \rho_1$ and $Cov\left(\epsilon_3, \epsilon_4\right) = \rho_2$, respectively.

Unfortunately, because we cannot observe the intensity of innovation, we estimate the systems (7) and (8) by substituting the latent variable $\hat{I}_{it}^{*,j}$, which is the predicted perceived probability of innovation type j. The dependent variables are binary indicators from the survey data that indicate whether firm i adopts innovation activities of type j. The probability of adopting innovation activities of type j is estimated according to the following equation:

$$I_{it}^{j} = \alpha + \gamma_1^j hum_{it} + \gamma_2^j soc_{it} + \gamma_3^j tec_{it} + \beta^j X_{it} + u_{it}^j \tag{9}$$

with the four different innovation practices $j = p, c, o, m$. In this case, I_i^j, equals 1 if firm i adopts innovation activities of type j, and 0 otherwise, and $I_i^{*,j}$ is an unobserved latent variable that is related to the innovative activity effort. Furthermore, hum_i, soc_i, and tec_i measure the share of employees in firm i that have completed more than 16 years of schooling within humanities, social sciences, and technical sciences, respectively. X_i contains other characteristics of the firm that are given by the (natural logarithm of the) number of employees, an export dummy, and industry dummies. u_i^j is a random error. In the regressions below, we apply more flexible versions of the relationship between the education shares and I_i^j, which includes the squared education shares and the interaction terms between education shares.

3.2. The Productivity Equation

When estimating the production function that is augmented with innovation activities modelling $I_1 = I_1\left(I_{it}^{*,c}, I_{it}^{*,o}\right)$ and $I_2 = I_2\left(I_{it}^{*,p}, I_{it}^{*,m}\right)$. The applied approach is designed to determine the 6 different combinations of the four innovation types. The 6 different probabilities of innovation are determined on the basis of the four predicted perceived innovation probabilities of the first stage of the estimation procedure.

Consequently, the second stage of the model productivity is estimated according to the following:

$$y_{it} = \phi + \sum_{\kappa=1}^{3} \beta_\kappa P_1 \left(I^{*,c}, I^{*,o}\right)_{\kappa t} + \sum_{\kappa=1}^{3} \beta_\kappa P_2 \left(I^{*,p}, I^{*,m}\right)_{\kappa t} + \tau(k-l)_{it} + \eta_1 sfe_{it} + \eta_2 mfe_{it} + \eta_3 lfe_{it} + v_{it} \tag{10}$$

where $P_1(.)_\kappa$ and $P_2(.)_\kappa$ refer to the perceived probability of innovation of combination κ that captures all 6 combinations of innovation. Thus, based on the set of combinations $(I^c, I^o) = \{(1,1), (1,0), (0,1)\}$ and $(I^p, I^m) = \{(1,1), (1,0), (0,1)\}$, the corresponding set of probabilities is measured as:

$$\begin{aligned} (P_{1,1}, P_{1,2}, P_{1,3}) &= \left\{ \left(\hat{I}^{*,c} \hat{I}^{*,o} \right), (\hat{I}^{*,c}(1 - \hat{I}^{*,o})), ((1 - \hat{I}^{*,c}) \hat{I}^{*,o}) \right\} \\ (P_{2,1}, P_{2,2}, P_{2,3}) &= \left\{ \left(\hat{I}^{*,p} \hat{I}^{*,m} \right), (\hat{I}^{*,p}(1 - \hat{I}^{*,m})), ((1 - \hat{I}^{*,p}) \hat{I}^{*,m}) \right\} \end{aligned}$$

Thereby, the 6 combinations of innovation are compared to firms without innovation activities; a combination that is excluded from the regression. y is the log of labour productivity and $k-l$ is log of capital per employee. sfe, mfe, and lfe are the shares of employees with 16 years of education and 18 or more years of education, respectively. v is a random error.

4. Data

The applied data set is based on a linked data set that consists of survey and register data from Statistics Denmark. We use the "Community Innovation Survey" (CIS-surveys) for Denmark for 2004 and 2007, and 2008. These surveys include questions regarding innovation activities in a representative sample of Danish firms. The firms are asked whether they are active in the following innovation types: product, process, organisational, and marketing innovations. Based on responses to these questions, we construct four binary variables that are used as dependent variables in the estimation of (9).[2]

An analysis that is founded on these four innovation types is consistent with the definition of innovation in the Oslo Manual: "An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organizational method in business practices, workplace organization or external relations." (OECD (2005), p. 46).

Table 1 displays the frequency of the possible combinations of innovation types separately for the three sample years and for the entire sample. 46 per cent of the firms do not have innovation activities. It is seen that many firm perform product and/or marketing innovation or organisational and/or process innovaton. For example, 3,039 firms – corresponding to approximately one-third of all firms in the sample – adopt product innovation; more than half of these firms also adopt marketing innovation. Moreover, 2,736 firms perform marketing innovation of which more than one third do not perform product innovation. Turning

[2]The firms in the 2007 survey encompass 41 per cent of employment and 46 percent of value added in the private sector.

to organisational and process innovation, 1,526 firms perform process innovation of which one fourth do not perform organisational innovation, and 3,630 firms perform organisational innovation of which as much as 70 percent do not perform process innovation. Actually, ten per cent of the total number of firms in the sample report that they adopt organisational innovation only. Similar patterns are found for the single year. In Table 2 the sample is divided into different sectors. Manufacturing firms have a higher frequency of innovation than retail and financial and real estate (FIRE) firms.

The survey data are linked to the Danish employer-employee matched data set that includes detailed educational information for individual employees. The sources are FIDA and IDA from Statistics Denmark. Using this data set, we are able to construct measures of the educational structure of employees in firms. Specifically, the variables *hum*, *soc*, and *tec* measure the share of employees with 16 years of education in humanities, social sciences, and technical sciences, respectively. Moreover, we construct the shares of employees according to the number of years of education completed, where $skilled$, sfe, mfe, and lfe denote the share of employees with 12 years, 14 years of education, 16 years of education, and 18 or more years of education, respectively. The dependent variable and the other explanatory variables all originate from the FIDA database. In Table 3 the minimum, maximum, median, mean, and standard deviation values are presented for all variables that are applied in the empirical analysis.[3]

Table 1: Descriptive statistics (first part): Innovation variables.

Types of Innovation				*2004*	*2007*	*2008*	*Entire Sample*	
							N. obs.	(%)
Product	**Process**	**Organization**	**Marketing**	116	229	228	573	5.9
Product	**Process**	**Organization**	-	170	43	74	287	3.0
Product	**Process**	-	-	56	43	41	140	1.4
Product	-	-	-	66	198	234	498	5.1
Product	-	-	**Marketing**	18	156	171	345	3.6
Product	**Process**	-	**Marketing**	21	49	59	129	1.3
Product	-	**Organization**	**Marketing**	86	290	302	678	7.0
-	**Process**	-	-	38	34	40	112	1.2
-	-	**Organization**	-	374	273	270	917	9.5
-	**Process**	-	**Marketing**	2	11	15	28	0.3
Product	-	**Organization**	-	180	90	119	389	4.0
-	**Process**	**Organization**	-	65	40	49	154	1.6
-	**Process**	**Organization**	**Marketing**	18	43	45	106	1.1
-	-	**Organization**	**Marketing**	75	265	186	526	5.4
-	-	-	**Marketing**	56	156	139	351	3.6
-	-	-	-	501	2,087	1,866	4,454	46.0
Total number of observations				1,842	4,007	3,838	9,687	100.0

[3]The description of these variables is reported in Appendix A.

Table 2: Descriptive statistics (second part): Innovation variables.

Types of Innovation				**Manufacturing**	**Construction**	**Retail**	**Transportation**	**Communication**	**Fire**	**Other**	**Entire sample**
Product	**Process**	**Organization**	**Marketing**	279	7	71	4	4	198	10	573
Product	**Process**	**Organization**	-	154	4	29	1	3	93	3	287
Product	**Process**	-	-	76	0	20	2	3	38	1	140
Product	-	-	-	196	0	107	3	4	179	9	498
Product	-	-	**Marketing**	132	0	81	2	4	124	2	345
Product	**Process**	-	**Marketing**	78	1	15	1	2	32	0	129
Product	-	**Organization**	**Marketing**	222	5	180	10	17	232	12	678
-	**Process**	-	-	65	3	7	2	5	30	0	112
-	-	**Organization**	-	228	76	254	52	9	288	10	917
-	**Process**	-	**Marketing**	9	0	5	1	0	12	1	28
Product	-	**Organization**	-	170	3	77	5	4	127	3	389
-	**Process**	**Organization**	-	74	5	14	9	1	48	3	154
-	**Process**	**Organization**	**Marketing**	45	3	15	4	0	37	2	106
-	-	**Organization**	**Marketing**	93	13	175	22	7	209	7	526
-	-	-	**Marketing**	68	5	140	9	5	120	4	351
-	-	-	-	1155	196	1,455	113	30	1,428	77	4,454
Total number of observations				3,044	321	2,645	240	98	3,195	144	9,687

Table 3: Descriptive statistics (third part): Registered data.

Variable	**Min**	**Max**	**Median**	**Mean**	**St.Dev.**
2004 (1,865 observations)					
y	12.77	23.63	16.97	17.11	1.60
k	1.10	17.70	9.08	9.11	2.18
l	0.00	10.03	4.03	4.08	1.52
hum	0.00	0.79	0.00	0.02	0.05
soc	0.00	1.00	0.01	0.05	0.09
tec	0.00	1.00	0.04	0.13	0.20
lfe	0.00	0.73	0.05	0.07	0.08
mfe	0.00	1.00	0.06	0.10	0.13
sfe	0.00	1.00	0.01	0.08	0.16
$skilled$	0.00	1.00	0.50	0.49	0.19
$manufacturing$	0.00	1.00	0.00	0.39	-
$construction$	0.00	1.00	0.00	0.05	-
$retail$	0.00	1.00	0.00	0.24	-
$transport$	0.00	1.00	0.00	0.04	-
$communication$	0.00	1.00	0.00	0.01	-
$fire$	0.00	1.00	0.00	0.26	-
$other$	0.00	1.00	0.00	0.01	-
$export$	0.00	1.00	1.00	0.67	-
2007 (4,007 observations)					
y	9.82	23.54	16.42	16.52	1.65
k	0.69	16.57	8.35	8.40	2.27
l	0.00	9.97	3.40	3.53	1.51
hum	0.00	0.76	0.00	0.02	0.06
soc	0.00	0.75	0.00	0.02	0.05
tec	0.00	1.00	0.03	0.12	0.21
lfe	0.00	1.00	0.04	0.07	0.09
mfe	0.00	1.00	0.05	0.10	0.14
sfe	0.00	1.00	0.01	0.08	0.16
$skilled$	0.00	1.00	0.48	0.47	0.21
$manufacturing$	0.00	1.00	0.00	0.31	-
$construction$	0.00	1.00	0.00	0.03	-
$retail$	0.00	1.00	0.00	0.27	-
$transport$	0.00	1.00	0.00	0.02	-
$communication$	0.00	1.00	0.00	0.01	-
$fire$	0.00	1.00	0.00	0.34	-
$other$	0.00	1.00	0.00	0.01	-
$export$	0.00	1.00	1.00	0.55	-
2008 (3,838 observations)					
y	9.57	23.37	16.34	16.48	1.69
k	0.00	16.53	8.23	8.33	2.39
l	0.00	9.91	3.30	3.47	1.57
hum	0.00	0.73	0.00	0.02	0.05
soc	0.00	1.00	0.01	0.05	0.11
tec	0.00	1.00	0.03	0.13	0.20
lfe	0.00	1.00	0.05	0.07	0.10
mfe	0.00	1.00	0.05	0.10	0.14
sfe	0.00	1.00	0.01	0.09	0.16
$skilled$	0.00	1.00	0.47	0.47	0.20
$manufacturing$	0.00	1.00	0.00	0.28	-
$construction$	0.00	1.00	0.00	0.02	-
$retail$	0.00	1.00	0.00	0.29	-
$transport$	0.00	1.00	0.00	0.02	-
$communication$	0.00	1.00	0.00	0.01	-
$fire$	0.00	1.00	0.00	0.35	-
$other$	0.00	1.00	0.00	0.02	-
$export$	0.00	1.00	0.00	0.60	-

It is evident that employees with 16 or more years of education represent an average of approximately 18-20 per cent of all employees. Technical studies represents approximately 12 per cent, social sciences about 5 per cent, whereas humanities represents 2-3 per cent for the average firm. In addition, the shares vary within the range from zero to one hundred per cent for most education types. The table also shows that approximately 30 per cent of the workforce in the average firm is represented by employees with a high level of education (i.e., with 14 or more years of education), whereas skilled workers constitutes around half of the employees.

5. Results

In this section, we present the empirical results of the analysis. In the first sub-section, the first-stage results of the estimation procedure are presented. Subsequently, we present the second-stage results. Finally, complementarity between innovation types are tested using a test of supermodularity.

5.1. First stage regressions

The first stage equations in (9) are estimated using bivariate probit model using the Stata *biprobit* code. Assuming that all of the firms that have $I_j^i = 0$ may exert some innovation effort, we estimate and predict the single innovation probability for the four innovation types. The results are presented in Tables 4 and 5 below. Moreover, for robustness check, we estimate the same system of equations by considering a single equation probit model. The latter model assumes that $Cov\,(\epsilon_1, \epsilon_2) = 0$ and $Cov\,(\epsilon_3, \epsilon_4) = 0$ instead of attaining values ρ_1 and ρ_2 as under the biprobit model. Table 4 presents the results for the probability of performing product and marketing innovation, whereas Table 5 presents the results process and organisational innovation.

The main estimation results for the probability model in (9) are that the intensive use of labourers with more than 16 years of education increases the probability of adopting innovation. A number of important results are evident from the two tables. First, the three types of education all play a role in knowledge production. Point estimates for technical sciences suggest a positive effect on the probability of innovation; an effect that varies across innovation types. Humanities and social sciences are also important for most innovation types except for process innovation. In general, however, the relationship between innovation type j and education shares is complex and includes squared terms and interaction terms. To gain more insight into the relationship between the shares of educated employees, we present the marginal effects on the innovation probabilities for different shares of educated employees. The result of this specification is presented in Figure 1.

It is clear from Figure 1 that education within technical sciences play an important role for the probabilities of firms having innovation activities. This is especially pronounced for product and process innovation. Social sciences play an important role for the probability of performing product, organisational, and marketing innovation. For marketing innovation, especially humanities and social sciences are important.

Table 4: Innovation equation (first part)

	(1) Probit		(2) Biprobit	
	I^p	I^m	I^p	I^m
k	0.04***	0.04***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
l	0.04***	0.04**	0.04***	0.04***
	(0.02)	(0.02)	(0.02)	(0.02)
$export$	0.29***	0.21***	0.29***	0.21***
	(0.03)	(0.03)	(0.03)	(0.03)
hum	2.91***	2.68***	2.90***	2.67***
	(0.51)	(0.48)	(0.51)	(0.48)
hum^2	-2.48***	-2.63***	-2.46***	-2.60***
	(0.77)	(0.68)	(0.77)	(0.65)
tek	2.86***	1.10***	2.84***	1.12***
	(0.26)	(0.25)	(0.26)	(0.25)
tek^2	-2.48***	-0.93**	-2.45***	-0.94***
	(0.33)	(0.32)	(0.32)	(0.31)
soc	2.98***	2.40***	3.01***	2.47***
	(0.44)	(0.43)	(0.43)	(0.44)
soc^2	-3.34***	-3.00***	-3.41***	-3.13***
	(0.77)	(0.78)	(0.74)	(0.80)
ht	-4.32***	-2.15	-4.23***	-2.11
	(1.38)	(1.34)	(1.34)	(1.31)
hs	-4.97***	-2.58	-4.93***	-2.62
	(1.75)	(1.58)	(1.68)	(1.61)
st	-0.74	-0.96	-0.81	-1.00
	(1.03)	(1.03)	(1.03)	(1.03)
$year\_2004$	0.11***	-0.31***	0.11**	-0.29***
	(0.04)	(0.04)	(0.04)	(0.04)
$year\_2007$	-0.13***	0.02	-0.13***	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
$Constant$	-1.81***	-1.29***	-1.33***	-1.24***
	(0.29)	(0.25)	(0.10)	(0.10)
ρ			0.63	
Log pseudolikelihood	-5388.27	-5503.58	-10150.09	
N. of obs 9,687				

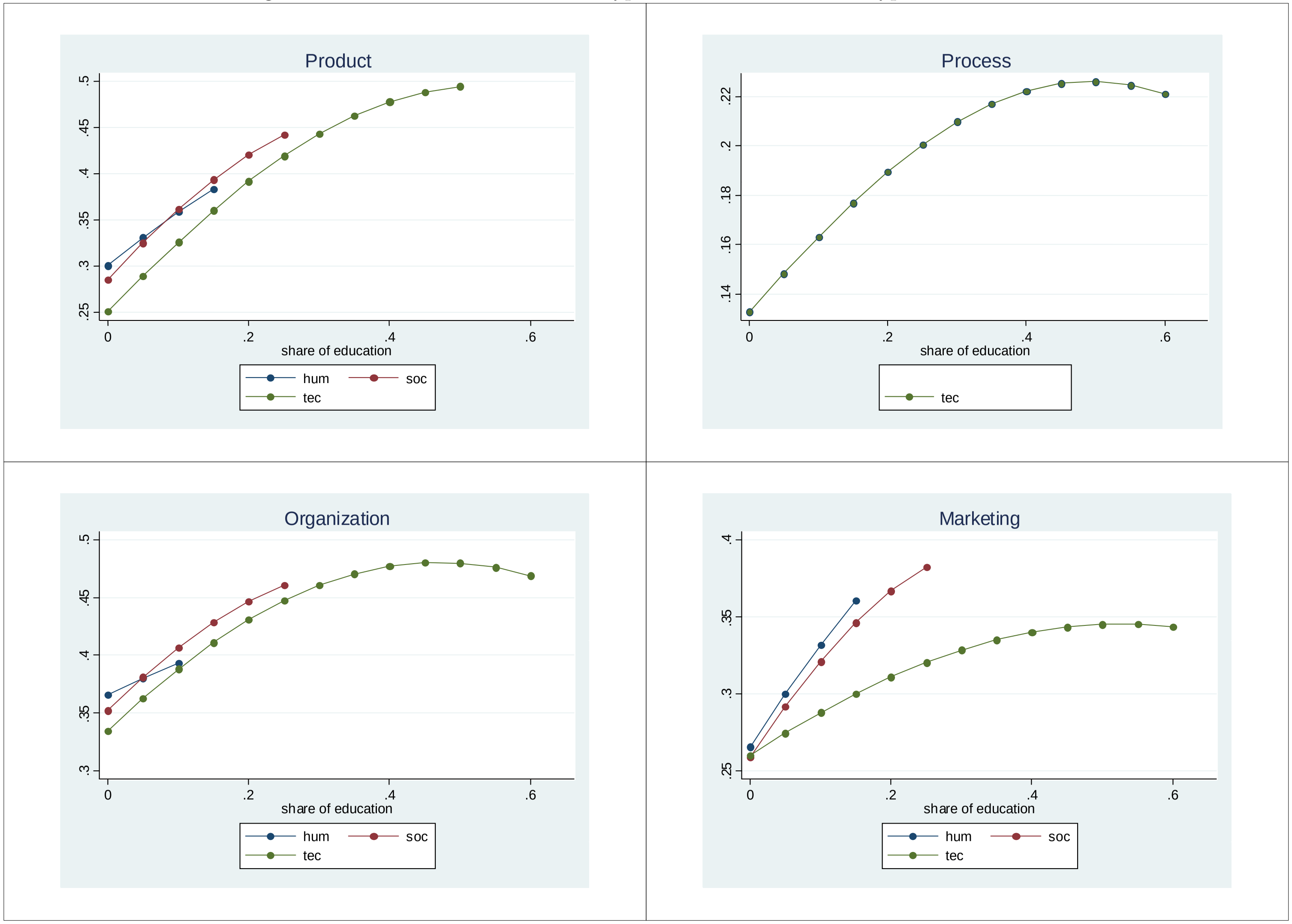
; * indicate significance at 5, and 1% respectively.
Standard error clustered at firm level.
All regressions controlled for sectoral dummies (not reported).

Table 5: Innovation equation (second part)

	(1) Probit		(2) Biprobit	
	I^c	I^o	I^c	I^o
k	0.08***	0.03***	0.08***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
l	0.05***	0.15***	0.05	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)
$export$	0.15***	0.16***	0.15***	0.16***
	(0.04)	(0.03)	(0.04)	(0.03)
hum	0.80	1.14**	0.88	1.12**
	(0.62)	(0.50)	(0.62)	(0.50)
hum^2	-0.28	-0.58	-0.39	-0.57
	(0.88)	(0.69)	(0.87)	(0.70)
tek	1.68***	1.91***	1.69***	1.91***
	(0.31)	(0.25)	(0.31)	(0.25)
tek^2	-1.67***	-1.89***	-1.65***	-1.89***
	(0.41)	(0.31)	(0.40)	(0.31)
soc	0.08	1.96***	0.18	2.00***
	(0.50)	(0.42)	(0.49)	(0.42)
soc^2	0.10	-2.30***	-0.11	-2.38***
	(0.79)	(0.70)	(0.78)	(0.70)
ht	-2.78	-2.32	-2.90	-2.35*
	(1.89)	(1.35)	(1.91)	(1.35)
hs	0.01	0.40	0.03	0.45
	(2.02)	(1.54)	(1.99)	(1.55)
st	0.80	-1.23	0.72	-1.29
	(1.13)	(1.00)	(1.13)	(1.01)
$year\_2004$	0.35***	0.59***	0.37***	0.59***
	(0.04)	(0.04)	(0.04)	(0.04)
$year\_2007$	-0.11***	-0.04	-0.11***	-0.04
	(0.04)	(0.03)	(0.04)	(0.03)
$Constant$	-2.32***	-1.54***	-1.86***	-1.66***
	(0.34)	(0.27)	(0.11)	(0.10)
ρ			0.49	
Log pseudolikelihood	-3757.94	-5787.13	-9236.91	
N. of obs 9,687				

; * indicate significance at 5, and 1% respectively.
Standard error clustered at firm level.
All regressions controlled for sectoral dummies (not reported).

Figure 1: The effects of educational types on innovation. Four types of education.



5.2. Productivity equation

The relationship between the combinations of innovation activities and productivity is provided by the estimations of the extended production function that is represented by (10) and displayed in Table 6, in which we consider different types of control variables, such as the physical input of production and the number of years of education. Furthermore, all of the regressions are controlled by year and sectoral dummies. The standard errors that we report are robust, are clustered by firms and bootstrapped after 50 replications. The first set of regressors considers the innovation part of the production function and is represented by the probabilities of adopting innovation practices obtained by the prediction of the biprobits reported in column (2) of Tables 4 and 5.

The results are presented in Table 6. In column 1 includes the predicted probability of performing product and marketing innovation, the predicted probability of performing product innovation but no marketing innovation, as well as the predicted probability of performing marketing innovation but no product innovation. The estimates compare the productivity effects of firms with innovation to firms without innovation. The estimates suggest that firms that perform product and marketing innovation have higher productivity that the other firms. Firms that perform product but no marketing innovation and firms that perform marketing innovation but no product innovation do not have productivity levels that differ from firms without innovation.

In column (2) of Table 6, we include predicted probabilities of organisational and process innovation, organisational innovation but no process innovation, and process innovation but no organisational innovation. The estimates suggest that firms that perform organisational and process innovation have higher productivity that baseline firms. Firms that perform organisational innovation but no process innovation also have significantly higher productivity levels but at a lower level than firms with both types of innovation. Finally, firms with process innovation but no organisational innovation do not have higher productivity levels than firms without any of the two innovation types.

In column (3) the probabilities from the two biprobit models are included in the regressions. It is seen that the results described above are robust to the inclusion of all 6 probabilities. These findings indicate strong complementarity between product and marketing innovation and between organisational and process innovation. Moreover, the results predicts an important role of organisational innovation only.

Our findings present the result that product and marketing innovation are important for productivity levels; a result that is new in the economic literature on innovation. Moreover, the remaining results are consistent with the findings of several contributions in the literature: Hall et al. (2012) and Hall (2011) demonstrate a strong positive role played by innovations in production practices, Polder et al. (2010), who consider a framework that is similar to our framework but utilise Dutch data, and Bloom and Van Reenen (2011) reveal the importance of organisation.

Once we consider the estimates for the physical input (represented by capital intensity kl and by the level of employment l), we observe that, while kl is positive and significant in all specifications, l shows small decreasing returns in columns 2 and 3.

Table 6: Productivity equation.

	(1)	(2)	(3)
$Pr\,(I^p = 1, I^m = 1)$	1.65***		1.13***
	(0.23)		(0.27)
$Pr\,(I^p = 1, I^m = 0)$	-0.32		-0.99
	(0.33)		(0.54)
$Pr\,(I^p = 0, I^m = 1)$	-0.31		-0.36
	(0.41)		(0.38)
$Pr\,(I^c = 1, I^o = 1)$		1.66***	1.23**
		(0.23)	(0.49)
$Pr\,(I^c = 1, I^o = 0)$		-0.34	0.13
		(0.90)	(1.12)
$Pr\,(I^c = 0, I^o = 1)$		1.36***	0.68**
		(0.21)	(0.34)
$skilled$	0.69***	0.68***	0.68***
	(0.16)	(0.16)	(0.16)
lfe	0.49***	0.52***	0.46***
	(0.16)	(0.16)	(0.17)
mfe	0.33**	0.30	0.32*
	(0.17)	(0.17)	(0.18)
sfe	0.64***	0.62***	0.63***
	(0.13)	(0.13)	(0.13)
$skilled^2$	-0.28**	-0.25	-0.27
	(0.14)	(0.14)	(0.14)
lfe^2	-0.38	-0.38	-0.31
	(0.22)	(0.22)	(0.23)
mfe^2	0.11	0.15	0.14
	(0.25)	(0.26)	(0.25)
sfe^2	-0.50	-0.49	-0.50
	(0.29)	(0.29)	(0.29)
kl	0.05***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)
l	-0.03	-0.08***	-0.05**
	(0.02)	(0.02)	(0.02)
l^2	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
$year\_2004$	0.07**	-0.33***	-0.10
	(0.03)	(0.04)	(0.08)
$year\_2007$	0.02	0.02	0.02
	(0.01)	(0.01)	(0.01)
$Constant$	12.23***	12.33***	12.33***
	(0.07)	(0.08)	(0.09)
R^2	0.49	0.49	0.49
N. obs	9,687		

; * indicate significance at 5, and 1% respectively.
Standard error clustered at firm level.
All regressions controlled for sectoral dummies (not reported)

5.3. Complementarity

An important assumption in the above analysis is complementarity between product and marketing innovation as well as between process and organisational innovation. This is an assumption that origins from the theoretical model and was implemented on the empircal estimations. However, since there are 4 innovation types, there are 6 pairs of innovation types that potentially could exhibit complementarity. For example, we exclude the possibility of complementarity between product and process innovation by assumption. In the remainder of this section we will shed light on how restrictive this assumption is. More precisely, we want to test the assumption by using the most sofisticated test of complementarity - namely the test for supermodularity as suggested by Milgrom and Roberts (1990).

We test for supermodularity following (Topkis (1998) and Mohnen and Roeller (2005)). In practice, we test whether the four innovation types are complementary by comparing pair innovation types. The applied method is described in Appendix D.

The results are presented in Table 8. The test statistics D for supermodularity as represented by (15) in Appendix D and obtained exploiting the point estimates described in Appendix C and presented in Table 7. We compare these values with the critical values of 1 per cent, respectively, which are provided by Kodde and Palm (1986). If the value is smaller than the lower bound, then we cannot reject the hypothesis that two innovation practices are complementary; if the value is greater than the upper bound, we reject the hypothesis. The result is uncertain if the value of D is between the two bounds. We obtain strong supermodularities in the combination of product and marketing innovation as well as process and organization innovation. These are the only two pair of innovation activities that we cannot reject as showing complementarity. These results strongly supports the theoretical model applied in this paper.

Table 7: Complementarity test between innovation practices.

	I^p	I^c	I^o	I^m
I^p	-	-	-	-
I^c	6.24	-	-	-
I^o	58.50	<u>0.00</u>	-	-
I^m	<u>4.42</u>	106.69	49.49	-
Critical values at 1%				
Lower bound (df = 1)	5.41			
Upper bound (df = 4)	12.01			

Underlined values denote innovation combinations for which the complementarity test is accepted.

6. Conclusion

In this study we provide insight regarding the relationship among educational, innovation practices and productivity. We considered a unique link between the Danish version of the CIS survey (for 2004, 2007 and 2008) and the Danish employer-employee data set, which contains detailed educational information pertaining to individual employees. We presented several novel elements both in terms of different types of innovation. We used a modified version of the three-stage framework that was introduced by Crepon et al. (1998); our application includes two stages only.

In the first stage, we estimate a knowledge production function for investigating the drivers of innovations. Based on the estimation of bivariate probability models, our results show that all of the education types with more than 16 years of schooling do increase the probabilities of adopting innovation practices. In particular, technical studies play important roles in all types of innovations, whereas humanities and social sciences are particularly relevant in product, organisational and marketing innovation.

In the second stage, we estimate an extended Cobb-Douglas production function that is augmented with the predicted probabilities of innovation types. We find that firms that jointly adopt product and marketing innovations are more productive than firms that adopt only product innovations but not marketing innovations or firms that adopt only marketing innovations but not product innovations. Furthermore, firms that adopt process and organisational innovation are more productive than firms that adopt organisational innovation but not process innovation that again have higher productivity levels than firm that perform process innovation but not organisational innovation. The latter group of firms with process innovation but no organisational innovation does not have higher productivity levels that firms without innovation. Finally, we studied complementarities between different innovation types by considering a test for supermodularity and find that the complementarity between production and marketing as well as between organisational and process innovation cannot be rejected. This latter result strongly supports the applied framework of the paper.

There are two broader implications of the paper. First, we show that the influence of education on productivity works through two channels; a direct effect working through production of goods and services and an indirect effect working through knowledge production. Second, we find that firms with innovation activities are more productive if they invest in the right combinations of innovation types. For example, firms with product innovation does not have higher productivity that firms without. Only firms with product and marketing innovation have higher productivity.

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Appendix A: Variable names and descriptions.

	Innovation variables		
I^p	equals 1 if the firm innovates in production, and 0 otherwise		
I^c	equals 1 if the firm innovates in process, and 0 otherwise	tb	$tec * bus$
I^o	equals 1 if the firm innovates in organization, and 0 otherwise	sfe	share of firm's employees with 14 years of education
I^m	equals 1 if the firm innovates in marketing, and 0 otherwise	mfe	share of firm's employees with 16 years of education
	Production function variables	lfe	share of firm's employees with 18 years of education
y	natural logarithm of labour productivity (log of value added in Danish krones per worker)	sfe^2	$sfe * sfe$
k	natural logarithm of physical capital	mfe^2	$mfe * mfe$
l	natural logarithm of labour input	lfe^2	$lfe * lfe$
kl	log of physical capital per worker		*Other variables*
	Education variables	$export$	equals 1 if the firms is an exporter, 0 otherwise
hum	share of firm's employees in humanities with more than 16 year of education	$manufacturing$	equals 1 if the firm belongs to manufacturing sector, 0 otherwise
soc	share of firm's employees in social science with more than 16 year of education	$construction$	equals 1 if the firm belongs to construction sector, 0 otherwise
tec	share of firm's employees in technical science with more than 16 year of education	$retail$	equals 1 if the firm belongs to retail sector, 0 otherwise
$skilled$	share of firm's skilled employees	$transport$	equals 1 if the firm belongs to transport sector, 0 otherwise
hum^2	$hum * hum$	$communication$	equals 1 if the firm belongs to communication sector, 0 otherwise
soc^2	$soc * soc$		
tec^2	$tec * tec$	$fire$	equals 1 if the firm belongs to financial and retail sector, 0 otherwise
$skilled^2$	$skilled * skilled$		
hs	$hum * soc$	$other$	equals 1 if the firm does not belong to the previous sector, 0 otherwise
ht	$soc * tec$		
st	$soc * tec$	$year\_2004$	equals 1 if the firm belongs to 2004 questionnaire, 0 otherwise
hs	$hum * soc$		
ht	$soc * tec$		
st	$soc * tec$	$year\_2007$	equals 1 if the firm belongs to
		2004 questionnaire, 0 otherwise	

Appendix B: CIS Questions on Research, Development and Innovation within a Company (2007)

1. **Product innovations**
   During the 2005-2007 period, did the company introduce product innovations in the form of:

   - **Product** that are new or significantly improved (excluding the simple resale of new products that were purchased from other companies and changes that are only of an aesthetic nature)?)

     Yes-No

   - **Services** that are new or significantly improved?

     Yes-No

2. **Process innovations**
   During the 2005-2007 period, did the company introduce process innovations in the form of:

   - New or significantly improved methods for the production of products or services?
     Yes-No
   - New or significantly improved logistics, delivery or distribution methods for the inputs, products or services for the company?
     Yes-No
   - New or significantly improved features to assist business processes? (systems or procedures in purchasing, maintenance, accounting or IT)
     Yes-No

3. **Organizational innovations**
   During the 2005-2007 period, did the company introduce organizational innovations in the form of:

   - New ways to organize business processes or procedures For instance quality management, supply chain management, lean production, education and training systems, knowledge management, and new organization of the product development process
     Yes-No
   - New methods for the organization of the workplace in terms of delegating responsibilities and decision-making For instance decentralization of decision making, job rotation, teamwork, integration or fragmentation of departments
     Yes-No

- New ways in which external relations to companies and public institutions are organized For instance alliances, partnerships, outsourcing, subcontracting/subcontractors

  Yes-No

4. **Marketing innovations**

- **Design**

  Significant changes in the design of a product or service (Excl. changes which only alter the functionality or ease-of- use of the product, and routine and seasonal changes such as change in fashion trends)

  Yes-No

- Significant changes in the wrapping of the product

  Yes-No

- **Promotions**

- Use of new media types or techniques for product promotion (such as new "media mix", new image of the product, new method for targeting promotion to the individual customer)

  Yes-No

- New marketing strategies to reach new groups of customer or new market segments

  Yes-No

- **Sales channels**

- New sales channels and methods for product placement (such as direct sales, internet sales, franchising, distribution license, new concept for the presentation of the product)

  Yes-No

- **Pricing**

  New methods of pricing the products or services (for instance discount systems, bonus systems, demand driven pricing)

  Yes-No

Appendix C: The Multivariate Probit

The knowledge production function is described by a set of probability response models for simultaneous innovation activities:

$$\begin{cases} I_{it}^{*,p} = \delta_1 Z_{it} + \epsilon_{1,it} \\ I_{it}^{*,m} = \delta_2 Z_{it} + \epsilon_{2,it} \\ I_{it}^{*,c} = \delta_3 Z_{it} + \epsilon_{3,it} \\ I_{it}^{*,o} = \delta_4 Z_{it} + \epsilon_{4,it} \end{cases}$$

where Z_{it} is a set of explanatory variables that are common for all four innovation equations. The second stage of the model productivity is estimated according to the following:

$$y_{it} = \phi + \sum_{\kappa=1}^{15} \beta_\kappa P\left(I^{*,p}, I^{*,c}, I^{*,o}, I^{*,m}\right)_{\kappa t} + \tau(k-l)_{it} + \eta_1 sfe_{it} + \eta_2 mfe_{it} + \eta_3 lfe_{it} + v_{it} \quad (11)$$

To conduct an additional test for complementarities - the test for supermodularity described below - we need estimates for the most complete specification of the extended production function presented in (11). In the first stage of the estimation of probabilities of innovation, we use a multivariate probit model using the Stata mvprobit code that was written by Cappellari and Jenkins (2003). This estimation method is based on the application of the Geweke-Hajivassiliou-Keane simulation method for maximum likelihood (Train (2003)) and allows for correlations among the error terms due to the influence of unobservable characteristics on different innovation choices. The results of the first stage are reported in Table 8 In the second stage we include the 15 probabilities of combinations of innovation types in the extended production function.

The results of the extended product function is presented in Table 9. We cannot easily interpret the point estimates of the predicted probabilities of innovation. However, the results confirm our previous findings on the signs and the significance of the non-innovation variables that are similar to the ones obtained in Table 6.

Appendix D: Test of Supermodularity

Because complementarity among innovation types is our main interest in the analysis, we also perform explicit tests of supermodularity (Topkis (1998), Milgrom and Roberts (1990) and Mohnen and Roeller (2005)). In practice, we test whether the four innovation types are complementary by comparing pair innovation types.

Given two innovation types, j and z, the production function $f(.)$ is supermodular if the following condition holds:

$$f\left(I^{*,j}\right) + f\left(I^{*,z}\right) \leq f\left(I^{*,j} \vee I^{*,z}\right) + f\left(I^{*,j} \wedge I^{*,z}\right) \ \forall j, z \quad (12)$$

where the first term on the right-side variable measures the componentwise maximum and the second term measures the componentwise minimum. Supermodularity is equivalent to

Table 8: Innovation equation: Multivariate Probit Estimation

	I^p	I^m	I^c	I^o
k	0.04***	0.04***	0.08***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
l	0.04**	0.03	0.04	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)
$export$	0.29***	0.21***	0.15***	0.15***
	(0.03)	(0.03)	(0.04)	(0.03)
hum	2.94***	2.66***	0.89	1.18
	(0.50)	(0.49)	(0.61)	(0.49)
hum^2	-2.48***	-2.51***	-0.29	-0.63
	(0.74)	(0.65)	(0.83)	(0.68)
tek	2.83***	1.05***	1.72***	1.90***
	(0.25)	(0.25)	(0.30)	(0.24)
tek^2	-2.42***	-0.86**	-1.68***	-1.85***
	(0.31)	(0.31)	(0.37)	(0.30)
sam	3.04***	2.51***	0.31	2.05***
	(0.43)	(0.44)	(0.49)	(0.42)
sam^2	-3.46***	-3.18***	-0.26	-2.39***
	(0.72)	(0.80)	(0.79)	(0.71)
qht	-4.20***	-1.73	-3.00	-2.19
	(1.32)	(1.34)	(2.00)	(1.32)
qhs	-5.07**	-2.95	-0.57	0.16
	(1.69)	(1.67)	(1.88)	(1.59)
qst	-0.96	-1.15	0.45	-1.61
	(1.02)	(1.04)	(1.10)	(0.97)
$year\_2004$	0.12***	-0.26***	0.37***	0.57***
	(0.04)	(0.04)	(0.04)	(0.04)
$year\_2007$	-0.13***	0.02	-0.12***	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)
$Constant$	-1.91***	-1.37***	-2.51***	-1.64***
	(0.31)	(0.28)	(0.36)	(0.31)
N. of obs 9,687				

*;**; *** indicate significance at 10, 5, and 1% respectively.
Standard error clustered at firm level.
All regressions controlled for sectoral dummies (not reported)

$\partial f\,(.)\,/\partial I^{*,j}\partial I^{*,z}$ if $f\,(.)$ is twice continuously differentiable. In other words, we are explicitly testing the two hypotheses that are presented in (5) and (6).

To perform the test, we use an approach that is similar to the approach that is adopted by Polder et al. (2010). For example, if we want to test for complementarity between product and process innovation, we consider the following inequality restrictions:

$$
\begin{array}{l}
f\left(0,I^{*,c},0,0\right)+f\left(I^{*,p},0,0,0\right)\leq f\left(I^{*,p},I^{*,c},0,0\right)+f\left(0,0,0,0\right)\Leftrightarrow\beta_{0100}+\beta_{1000}\leq\beta_{1100}+\beta_{0000}\\
f\left(0,I^{*,c},I^{*,o},0\right)+f\left(I^{*,p},0,I^{*,o},0\right)\leq f\left(I^{*,p},I^{*,c},I^{*,o},0\right)+f\left(0,0,I^{*,o},0\right)\Leftrightarrow\beta_{0110}+\beta_{1010}\leq\beta_{1110}+\beta_{0010}\\
f\left(0,I^{*,c},0,I^{*,m}\right)+f\left(I^{*,p},0,0,I^{*,m}\right)\leq f\left(I^{*,p},I^{*,c},0,1\right)+f\left(0,0,0,I^{*,m}\right)\Leftrightarrow\beta_{0101}+\beta_{1001}\leq\beta_{1101}+\beta_{0001}\\
f\left(0,I^{*,c},I^{*,o},I^{*,m}\right)+f\left(I^{*,p},0,I^{*,o},I^{*,m}\right)\leq f\left(I^{*,p},I^{*,c},I^{*,o},I^{*,m}\right)+f\left(0,0,I^{*,o},I^{*,m}\right)\Leftrightarrow\beta_{0111}+\beta_{1011}\leq\beta_{1111}+\beta_{0001}
\end{array}
\tag{13}
$$

where the βs refer to the coefficients that are obtained using the estimation of the different probabilities of innovation that are obtained by the production function. Following Kodde and Palm (1986) when considering the case of complementarity between process and product innovation, we define $\gamma = [\beta_{1111}, \ldots \beta_{0000}]$ and the mapping matrix, e.g., for (13):

$$
S = \left[\begin{array}{cccccccccccccccc}
0 & 0 & 0 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & -1 \\
0 & -1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & -1 & 0 & 0 \\
0 & 0 & -1 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & -1 & 0 \\
-1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 \\
 & & & & & & & & & & & & & & &
\end{array}\right]. \tag{14}
$$

The test statistics for supermodularity is defined as follows:

$$
D = (S\tilde{\gamma} - S\hat{\gamma}) \left(S^{'} cov\left(\hat{\gamma}\right) S\right)^{-1} (S\tilde{\gamma} - S\hat{\gamma}) \tag{15}
$$

where $\tilde{\gamma} = argmin \left(S\gamma - S\hat{\gamma}\right)^{'} \left[S^{'} cov\left(\hat{\gamma} S\right)\right]^{-1} \left(S\gamma - S\hat{\gamma}\right)$. The value of D is compared with the upper and the lower values of the Wald criteria for jointly testing equality and inequality restrictions obtained by Kodde and Palm (1986).

Table 9: Productivity equation: probabilities obtained by a multivariate probit.

$p(1111)$	-0.02
	(2.49)
$p(1110)$	3.29
	(1.69)
$p(1101)$	39.67**
	(16.17)
$p(1011)$	-4.52
	(2.51)
$p(0111)$	6.32
	(5.80)
$p(1100)$	-23.21***
	(8.10)
$p(1010)$	2.53**
	(1.04)
$p(1001)$	-2.44
	(2.07)
$p(0110)$	0.15
	(1.97)
$p(0101)$	-18.10***
	(5.49)
$p(0011)$	7.58**
	(2.33)
$p(1000)$	3.25**
	(1.40)
$p(0100)$	12.56***
	(2.63)
$p(0010)$	-2.43
	(1.16)
$p(0001)$	-0.31
	(0.71)
$qski$	0.66***
	(0.15)
$qlvu$	0.33
	(0.17)
$qmvu$	0.21
	(0.17)
$qkvu$	0.55***
	(0.13)
$qlvusq$	-0.24
	(0.22)
$qmvusq$	0.17
	(0.25)
$qkvusq$	-0.42
	(0.29)
$qskisq$	-0.26
	(0.14)
kl	0.03***
	(0.01)
l	0.00
	(0.03)
l^2	-0.01***
	(0.00)
$year\_2004$	0.01
	(0.11)
$year\_2007$	0.05***
	(0.02)
$Constant$	11.96***
	(0.14)
R^2	0.14
N. of obs	9,687

; * indicate significance at 5, and 1% respectively.
Standard error clustered at firm level.
All regressions controlled for sectoral dummies (not reported)