Innovation and Productivity in the Food vs. the High-Tech Manufacturing Sector

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Abstract:

The food sector is considered a mature and a research and development (R&D) extensive industry. Nevertheless, also food companies face numerous challenges and cannot abstain from innovation activity if they want to keep their competitive stance. We examine the impact of innovation on labor productivity in European food companies in comparison to results for firms operating in high-tech sectors. The central motivation of our study is that the observed low R&D intensity in the food sector should be mirrored in different productivity effects of innovation when compared to the high-tech sector. We use microdata from the European Union's "Community Innovation Survey" (CIS) and apply an endogeneity-robust multi-stage model that has been applied by various recent studies. Our results point out major differences between the examined subsectors. While we find strong positive effects of innovation on labor productivity for food firms, we find insignificant effects in the high-tech sector. This suggests that the returns to innovation might be best evaluated separately by sector rather than for the manufacturing sector as a whole.

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Keywords: Innovation, productivity, food industry, high-tech vs. low-tech

JEL codes: D24, L6, O3

Abstract

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Introduction

The food sector is one of the most important subsectors of the European Union's (EU) manufacturing sector in terms of employment and aggregate value added (Eurostat 2017b). At the same time, it is regarded as a mature and therefore technology extensive industry. Nevertheless, food processing companies face not less challenges from external sources than firms in other sectors, be it by intensive competition, input and output market price volatility, product quality requirements, or changing customer needs. For these reasons, food companies cannot abstain from innovation activity if they want to keep their competitive stance. We argue that the observed differences in research and development (R&D) intensity among subsectors of the manufacturing sector are a result of differing returns to innovation and differing innovation behavior. Therefore, returns to innovation might be best studied separately by subsector. Our study contributes by uncovering these differences through analysis of the relationships between innovation inputs and outputs and labor productivity in the special case of the food sector and in comparison to two high-tech sectors (chemicals and pharmaceuticals as well as computer, electronic, and optical products). Although the model and the data we employ have been used in various other studies, to our best knowledge, our research question has not been addressed before and our study therefore provides genuine insight into innovation behavior and innovation effects in the food sector in contrast to the high-tech sector.

Background and Related Literature

Eurostat (2017a) classifies the subsectors of the manufacturing sector according to their "technological intensity" into high-technology, medium-high-technology, medium-low-technology, and low-technology. Along with various other traditional industries, the food sector is classified as a low-technology sector. At the level of the 2-digit NACE classification, the only two high-technology subsectors are the pharmaceuticals industry and the manufacture of computer, electronic, and optical products. An example for a medium-high-technology sector is the manufacture of chemicals and chemical products. A similar classification is provided by the OECD (2011). Following Pakes and Schankerman (1984) the reasons for disparities in R&D intensity between sectors can be subsumed into three categories: product market demand, technological opportunity, and appropriability conditions. In the case of the European food sector the effect of market demand can be expected to be twofold: on the one hand aggregate demand is high compared to other sectors, on the other hand growth rates are low and consumers behave conservative when it comes to new product developments. Another important factor can be seen in technological opportunity: firms in high-tech sectors profit to a greater extent from scientific advances generated outside the firm, while food firms are confined by the physical relationship between production inputs and outputs. One has to keep in mind that all these factors only have an indirect effect on the decision of a firm's innovation input via the expected returns of the innovation input. If firms behave as profit maximizers, the effort they put into their innovation activities should be determined by the returns they expect from these investments (Pakes and Schankerman 1984).

Another point discussed in the literature is in how far low-tech firms differ from high-tech firms in the way they generate innovation output from innovation input. Schiefer et al. (2009) remark that food firms tend to be focused on process innovations and therefore source a significant share of their innovations from upstream industries, e. g. suppliers of equipment. Galizzi and Venturini (1996) find comparably small correlations between innovation and R&D for food firms, which could imply that for food firms their existing knowledge stock is more important source for innovation than R&D related activities. Mairesse and Mohnen (2005) examine the importance of R&D in the innovation production process of high-tech vs. low-tech (excluding food) firms. Contrary to Galizzi and Venturini they find that on average, R&D intensity can be attributed greater significance for innovation output of low-tech firms compared to high-tech firms. A consequence from these considerations can be that when the effects of and influences on innovation are studied, coefficients should be allowed to vary between subsectors.

When it comes to measuring the impact of innovation activity in the production function, one question to be asked is whether R&D is the appropriate measure. The general argument against R&D as an innovation indicator is that R&D efforts represent only a primary step (the innovation input) in the whole innovation process. An appropriate measure would somehow reflect innovation output, e. g. the number (and ideally innovation content) of new products and processes. To account for this, many studies adopted the model of Crépon, Duguet, and Mairesse (1998, CDM hereafter). This multi-stage model has the advantages of taking into account both selectivity and simultaneity issues and of picturing the whole innovation process from the decision to engage in R&D to the effect of innovation output on productivity. Examples of studies employing the CDM model on manufacturing firms (and services in some studies) include Griffith et al. (2006), Castellacci (2011), Hashi and Stojčić (2013), Lööf and Heshmati (2002), Raffo, Lhuillery, and Miotti (2008), Siedschlag and Zhang (2014), and Tevdovski, Tosevska-Trpcevska, and Disoska (2017). Most of these studies confirm a positive effect of innovation output on productivity. The only exceptions can be found by Griffith et al. (2006) and Raffo, Lhuillery, and Miotti (2008) who find negative but insignificant effects in some regressions. The aforementioned studies all focus on the manufacturing sector as a whole. An example of a CDM model specifically in the food sector can be found in the study by Acosta, Coronado, and Romero (2015). For Spanish firms they find a positive elasticity of productivity with respect to innovation output of about 30 % for various innovation output indicators. We are not aware of other studies employing the CDM model on the food sector as a separate sample.

A close study to ours in terms of a comparison of the food vs. the whole manufacturing sector was conducted by Triguero, Córcoles, and Cuerva (2013) who aim at uncovering differences in persistence of innovation activity. We are not aware of studies focusing on the difference in the effect of innovation activity on (labor) productivity. Various studies that work with the CIS dataset include sector dummy variables that allow for scaling of the functions in different sectors (examples). This, however, does not allow for different slopes, which seems crucial considering the suspected heterogeneity in innovation behavior among subsectors of the manufacturing industry.

Model and Hypotheses

Adopting the framework of the CDM literature, we assume that separately from a firm's production process, we can describe the knowledge production process, which transforms innovation inputs (predominantly R&D efforts) into innovation outputs (new products and processes). The knowledge production for firm i can be represented by

$$g_i = r_i \alpha_1 + x'_i \alpha_2 + \epsilon_{1i}, \qquad (1)$$

with innovation output g_i, R&D effort r_i, additional variables affecting innovativity contained in the row vector $x_i{}'$, and their corresponding parameters α_1 and α_2. ϵ_{1i} is an idiosyncratic error. We assume that a firm's production can be described by Cobb-Douglas technology incorporating the single (traditional) production input labor. We assume further that part of a firm's efficiency can be explained by its innovation output. In natural logarithms the production function is then given by

$$q_i = \alpha_3 l_i + \alpha_4 g_i + u_i + \epsilon_{2i}, \qquad (2)$$

with q_i, the ith firm's logarithmic output, logarithmic labor input l_i, output elasticity of labor α_3, output elasticity with respect to innovation α_4, residual efficiency u_i, and an idiosyncratic error ϵ_{2i}. Under the assumption of constant returns to scale and profit maximization, theory predicts that output elasticities equal the cost shares of the respective inputs. If also innovation output does not play the same role in the production process as the traditional production inputs like labor, we can express some intuitive expectations about differences in the effect of innovation output on production output in different manufacturing subsectors. Firms can be expected to choose their R&D efforts according to the returns the innovation output generates. Specifically, if we regard R&D expenditures as the cost of innovation and keeping in mind the high R&D intensity in high-tech sectors, we could assume that firms in high-tech sectors show on average larger α_4 than food firms. This assumption, however, might only hold in the long run. Also, strategic considerations supposedly play a role in how a firm chooses its level of R&D efforts. From a long-run perspective, we hypothesize that firms in high-tech subsectors show on average higher output elasticity with respect to innovation output. We acknowledge, however, that this hypothesis might not hold in the short-run.

Data and Empirical Strategy

The EU's Community Innovation Survey (CIS) was started in 1992 and since then collects data relating to innovation activity of European firms at approximately two-year intervals. National statistical offices conduct the survey following a harmonized questionnaire separately for their country and the datasets are compiled to one by Eurostat. The dataset contains general firm characteristics like turnover and the number of employees along with data on the innovation activity of the firm, e.g. the number of new products and processes implemented as well as innovation inputs and information sources for innovation. We use data from the latest available CIS wave (CIS 2014) which refers to the study period of 2012 to 2014. We analyze the data as a cross-section since panel identifiers are not implemented in the CIS methodology.[1] For 2014, microdata from 21 member states were available for analysis in Eurostat's Safe Center in Luxemburg. For our study we use data from Germany, Spain, France, and Italy. With this country selection we aim at selecting a sample of manufacturing firms with a technology level that is to a large extent comparable across countries. Partly, the country selection is also driven by data availability, since not every member state included all variables in its national survey. Detailed descriptive statistics by sector and country are given in Table 7 and Table 8 in the appendix. What is apparent from the tables is that although there is some variation within

[1] To our knowledge, panel identifiers are implemented starting from CIS 2014 so that first panel data estimations will be possible with the consecutive CIS wave.

sectors across countries, key variables like turnover per employee, R&D expenditures per employee, or the share of firms that introduced a product innovation are clustered by sectors rather than by countries. This observation further encourages our intention to analyze the data separately by sector rather than by country. Detailed variable descriptions can be found in the appendix.

In estimating the impact of innovation on labor productivity with the CIS dataset, one has to cope with potential endogeneity. It must be assumed that there are variables not included in the CIS survey that impact both innovation activity and productivity. Further, it is likely that productivity and innovation activity are simultaneously determined by influencing each other. Crépon, Duguet, and Mairesse (1998) propose a remedy to these endogeneity problems by estimating several subsequent equations depicting the whole innovation process of a firm. First, the determinants of the R&D intensity (the innovation inputs, expressed as R&D expenditure per employee) of a firm are evaluated. Because the structure of the CIS questionnaire dictates that only the subsample of firms with any innovation activity give information on R&D expenditures, this estimation step is performed as a Heckman selection model to avoid selection bias. Formally,

$$h_i^* = public_i'\beta_1 + x'_i\beta_2 + e_{1i} \tag{3}$$

represents the selection equation with the latent variable h_i^*, which takes a value above zero for firms deciding to invest in formal R&D and to report their R&D expenditures ($h_i = 1$). Analogously, $h_i^* \leq 0$ for firms not engaging in formal R&D and/or not reporting R&D expenditures ($h_i = 0$). The vector x_i' comprises control variables that we include in all estimation steps. Specifically, it includes dummy variables for seven firm size classes according to the number of employees, sector and country dummy variables, as well as dummy variables for belonging to an enterprise group, having a foreign home office, and operation on local, national, or international markets. $public_i'$ represents dummy variables for the use of public funding on local, national or EU programs. The second equation of the Heckman model describes the intensity of R&D activities, with

$$r_i^* = public_i'\beta_3 + x'_i\beta_4 + e_{2i} \tag{4}$$

describing the R&D intensity expressed as the natural logarithm of R&D expenditures per employee, which is not observed when $h_i = 0$ and equal to r_i when $h_i = 1$. Because we cannot think of a reasonable exclusion restriction, we include with $public_i'$ and x_i the same variables as the selection equation. We want to note already here and show later with a robustness check, that the interpretation of our results did not change with an alternative specification of the Heckman model. Apart from the dummy variables describing the use of public funding, all variables are included in the subsequent estimation steps (the knowledge production function and the productivity equation). That is, we rely on the public funding dummy variables as excluded instruments for the innovation input. Examples for other studies that use the public funding variables for at least one of the equations in the Heckman model include Acosta, Coronado, and Romero (2015), Griffith et al. (2006), Hashi and Stojčić (2013), Raffo, Lhuillery, and Miotti (2008), as well as Tevdovski, Tosevska-Trpcevska, and Disoska (2017).

In the second step of the CDM model, the innovation inputs are connected to the innovation outputs in form of the knowledge production function. The CIS questionnaire incorporates several innovation output indicators, whereas most of them come in the form of binary variables indicating the introduction e. g. of a product or a process innovation. The knowledge production function can then take the form of a probit estimation, described by

$$g_i = \widehat{r_i^*}\beta_5 + coop_i'\beta_6 + x'_i\beta_7 + e_{3i}, \tag{5}$$

where g_i is either the binary process or product innovation indicator. To encounter endogeneity in this step, as the innovation input the predicted R&D intensity $\widehat{r_i^*}$ is used here in place of the observed R&D intensity. Following Griffith et al. (2006) we predict r_i^* for the whole sample and not just the R&D reporting firms, implying that this measure covers the entirety of efforts a firm puts into its innovation process and not just the innovation inputs represented by formal R&D. We include with x_i' the same control variables as in the Heckman model, alongside with dummy variables of innovation cooperation ($coop_i'$) as excluded instruments for the innovation output because we can assume that cooperation in innovation activities has an effect on the innovativity of a firm.

The last step consists of incorporating the innovation output in a production function, which allows the evaluation of production output elasticity with respect to innovation output. We estimate the production function in the productivity form, i. e. with labor productivity as the dependent variable while we control for deviations from constant returns to scale by incorporating firm size dummies as explaining variables. Again, since innovation output cannot be regarded as exogenous in this equation, the predicted innovation output (predicted probability) from the second estimation step is used as an explanatory variable. Formally, this step is described as

$$y_i = \widehat{g_i}\beta_8 + x'_i\beta_9 + e_{4i}, \tag{6}$$

where y_i is the natural logarithm of turnover per employee, $\widehat{g_i}$ is the predicted innovation output, and x_i' contains the same control variables as in the previous steps.

We estimate the model pooled by countries and separately for each one of the three selected sectors, namely the food sector as a low-tech sector, and as representatives of high-tech sector the chemicals and pharmaceuticals industry (divisions 20 and 21 of NACE Rev. 2) forming a pooled sample, along with the sector of computer, electronic and optical products (division 26 of NACE Rev. 2, henceforth the "electronics sector"). This estimation strategy not only allows for differing returns to R&D and innovation across subsectors but also for possible differences in the parameters of innovation determinants and control variables included in the estimations. In other words, we allow for heterogeneity in innovation behavior across subsectors to a greater extent than as it would be possible with pooled regressions including subsector interaction variables.

Results

Table 1 and Table 2 show the results for the Heckman selection model of the food sector and the two high-tech sectors, respectively. Across sectors no differences of remarkable magnitude are evident in this stage. As expected the public funding dummies show a positive (in most cases significant) effect on both the propensity and the intensity of R&D. The results point out partly significant differences between countries, but we are careful with the interpretation of country differences because these might be a result of differences in questionnaire design. The most prominent difference is that firm size seems to play a much more important and consistent role as a determinant of the R&D intensity in the food sector compared to the high-tech sectors. R&D intensity decreases almost monotonically with the size of food firms, while this trend is not clear-cut for the high-tech sectors. as a determinant of the R&D intensity in the food sector compared to the high-tech sectors. R&D intensity decreases almost monotonically with the size of food firms, while this trend is not clear-cut for the high-tech sectors.

Table 1: Results of the Heckman Selection Model for the Food Sector

	Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.
Public funding				
Local level	0.435***	(0.049)	0.439***	(0.129)
National level	0.569***	(0.049)	0.801***	(0.141)
EU	0.221**	(0.099)	0.126	(0.188)
Enterprise group	0.138***	(0.025)	0.347***	(0.093)
Foreign homeoffice	-0.035	(0.046)	0.211	(0.154)
Markets				
Local	-0.015	(0.042)	-0.191	(0.148)
National	0.205***	(0.033)	-0.052	(0.165)
EU	0.060**	(0.030)	0.125	(0.121)
Other	0.100***	(0.028)	0.255***	(0.097)
Country				
Germany	reference			
Spain	-0.272***	(0.045)	0.136	(0.190)
France	-0.189***	(0.046)	0.235	(0.196)
Italy	-0.138***	(0.049)	0.166	(0.203)
Firm size (number of employees)				
10-19	reference			
20-49	0.077***	(0.027)	-0.588***	(0.126)
50-99	0.098***	(0.032)	-0.593***	(0.135)
100-249	0.204***	(0.037)	-1.096***	(0.141)
250-499	0.314***	(0.044)	-1.297***	(0.155)
500-999	0.351***	(0.063)	-1.197***	(0.201)
≥1000	0.525***	(0.082)	-1.217***	(0.255)
3-digit NACE	included		included	
Rho	-0.292	0.188		
Log-likelihood	-4217.4			
Number of observations	3334			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 2: Results of the Heckman Selection Model for the High-Tech Sector

	Chemicals and Pharmaceuticals				Computer, electronic and optical products			
	Selection equation		Intensity equation		Selection equation		Intensity equation	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Public funding								
Local level	0.239***	(0.043)	0.185*	(0.101)	0.013***	(0.003)	0.249***	(0.086)
National level	0.388***	(0.035)	0.351***	(0.078)	0.015***	(0.004)	0.470***	(0.088)
EU	0.194***	(0.065)	0.360***	(0.121)	0.068***	(0.022)	0.462***	(0.091)
Enterprise group	0.026	(0.022)	0.312***	(0.088)	0.002	(0.002)	0.315***	(0.103)
Foreign homeoffice	-0.040*	(0.023)	-0.201**	(0.090)	-0.001	(0.002)	-0.023	(0.128)
Markets								
Local	0.069***	(0.027)	-0.101	(0.112)	0.003	(0.002)	-0.314***	(0.106)
National	0.077**	(0.032)	0.182	(0.196)	0.004	(0.003)	-0.971***	(0.199)
EU	0.083***	(0.026)	-0.217	(0.141)	0.003	(0.002)	0.128	(0.169)
Other	0.089***	(0.022)	0.230**	(0.102)	0.005***	(0.002)	0.539***	(0.15)
Country								
Germany	reference				reference			
Spain	-0.178***	(0.041)	-0.419***	(0.129)	-0.009***	(0.003)	0.046	(0.12)
France	-0.191***	(0.044)	-0.190	(0.135)	-0.005**	(0.003)	0.159	(0.131)
Italy	-0.152***	(0.043)	-0.552***	(0.14)	-0.007**	(0.003)	-0.282**	(0.127)
Firm size (number of employees)								
10-19	reference				reference			
20-49	0.024	(0.023)	-0.109	(0.099)	-0.002	(0.002)	-0.408***	(0.11)
50-99	0.027	(0.027)	-0.344***	(0.125)	0.001	(0.002)	-0.614***	(0.143)
100-249	0.077***	(0.03)	-0.265**	(0.119)	0.000	(0.002)	-0.447***	(0.146)
250-499	0.176***	(0.037)	-0.245*	(0.131)	0.004	(0.003)	-0.356**	(0.158)
500-999	0.223***	(0.053)	-0.014	(0.169)	0.009*	(0.005)	-0.116	(0.229)
≥1000	0.266***	(0.073)	0.393**	(0.175)	0.054***	(0.018)	0.106	(0.19)
3-digit NACE	included		included		included		included	
Rho	-0.117	0.152			-0.105	0.09		
Log-likelihood	-3483.1				-1660.6			
Number of observations	2111				1066			

Notes: Standard errors (S. E.) are robust. Shown are marginal effects on the probability of positive R&D expenditures (selection equation) and marginal effects on expected R&D intensity conditional on positive R&D (intensity equation). Levels of significance are ***1%, **5%, *10%.

Table 3 reports the results of the knowledge production function for the product innovation indicator. While we conducted the analysis for product and process innovation in parallel, we present detailed results only for product innovation since the results in the knowledge production function and also in the subsequent productivity equation were almost identical for the product and the process innovation indicator.[2] Also in this stage, the results are similar

[2] The likely reason for this is that the same instrumental variables are used for both innovation indicators and the relationship between instrumental variables and the two innovation indicators is similar, leading to a high

across the sectors. R&D intensity is positively related to the introduction of a product innovation in all sectors, as to be expected. R&D intensity seems to be more important for a product innovation in the food than in the high-tech sectors. Again, firm size seems to play a more important role for the innovativity of a firm in the food sector compared to firms in the high-tech sectors: With a given level of R&D intensity, large food firms are far more likely to introduce a product innovation than smaller food firms, while this effect is less pronounced for firms in the high-tech sectors.

correlation between the two. High correlation between the innovation indicators is also observed by Raffo, Lhuillery, and Miotti (2008), Acosta, Coronado, and Romero (2015), Tevdovski, Tosevska-Trpcevska, and Disoska (2017).

Table 3: Results of the Knowledge Production Function by Sector

	Food		Chemicals and Pharmaceuticals		Computer, electronic and optical products	
	Coef.	b. S. E.	Coef.	b. S. E.	Coef.	b. S. E.
R&D intensity	0.502***	(0.082)	0.258***	(0.098)	0.302***	(0.049)
Cooperation partners						
Other enterprise group members	0.237***	(0.048)	0.172***	(0.04)	0.170**	(0.073)
Suppliers	0.182***	(0.052)	0.133***	(0.044)	0.046	(0.047)
Customers	0.106	(0.075)	0.106**	(0.052)	-0.02	(0.057)
Competitors	0.019	(0.067)	0.082	(0.054)	-0.076	(0.06)
Consultants	0.154***	(0.059)	0.016	(0.053)	0.057	(0.059)
Universities	0.015	(0.055)	0.079	(0.048)	0.078*	(0.04)
Government/public or private research institutes	0.078*	(0.045)	0.066	(0.045)	0.111*	(0.059)
Enterprise group	-0.04*	(0.024)	-0.102**	(0.045)	-0.075*	(0.045)
Foreign homeoffice	-0.091*	(0.05)	-0.016	(0.04)	-0.028	(0.051)
Markets						
Local	0.135***	(0.039)	0.196***	(0.049)	0.153***	(0.034)
National	0.205***	(0.03)	0.065	(0.065)	0.322***	(0.08)
EU	0.043	(0.028)	0.204***	(0.05)	0.035	(0.041)
Other	-0.011	(0.036)	0.038	(0.039)	-0.064	(0.043)
Country						
Germany	reference		reference		reference	
Spain	-0.402***	(0.043)	-0.156***	(0.056)	-0.211***	(0.043)
France	-0.385***	(0.044)	-0.168***	(0.054)	-0.173***	(0.048)
Italy	-0.278***	(0.038)	-0.035	(0.073)	-0.013	(0.047)
Firm size (number of employees)						
10-19	reference		reference		reference	
20-49	0.371***	(0.059)	0.018	(0.038)	0.132***	(0.045)
50-99	0.409***	(0.064)	0.119**	(0.061)	0.206***	(0.065)
100-249	0.737***	(0.106)	0.132***	(0.045)	0.161***	(0.052)
250-499	0.940***	(0.131)	0.246***	(0.066)	0.170**	(0.068)
500-999	0.929***	(0.139)	0.138**	(0.058)	0.120	(0.124)
≥1000	1.016***	(0.157)	0.209**	(0.091)	0.168*	(0.089)
3-digit NACE	included		included		included	
Pseudo-R²	0.235		0.159		0.263	
Log-likelihood	-1,601.2		-1,219.3		-465.0	
Number of observations	3,334		2,111		1,066	

Notes: Standard errors are bootstrapped (b. S. E.). Shown are marginal effects at sample means on the probability of the introduction of a product innovation. Levels of significance are ***1%, **5%, *10%.

Our main interest lies in the output elasticity with respect to innovation for firms in each sector. Results of the productivity equations are shown in Table 4. We again only show results for the product innovation indicator since the results for the process innovation indicator do not differ substantially. For food firms, product innovation has a positive effect and causes an increase in labor productivity by approximately 42%. This seems high but lies well in the range of coefficients usually reported in other studies.[3] The most surprising finding is that for both high-tech sectors, no positive effect of innovation output on labor productivity is evident. The coefficients even show a negative sign, however, not statistically significant.

Table 4: Results of the Productivity Equation by Sector

	Food		Chemicals and Pharmaceuticals		Computer, electronic and optical products	
	Coef.	b. S. E.	Coef.	b. S. E.	Coef.	b. S. E.
Product innovation	0.423***	(0.100)	-0.149	(0.122)	-0.024	(0.133)
Enterprise group	0.302***	(0.041)	0.384***	(0.045)	0.169***	(0.065)
Foreign homeoffice	0.100	(0.065)	0.182***	(0.041)	0.181***	(0.056)
Markets						
Local	0.058	(0.057)	0.166***	(0.059)	0.044	(0.052)
National	0.348***	(0.054)	0.223**	(0.098)	0.100	(0.109)
EU	0.231***	(0.048)	0.016	(0.066)	0.303***	(0.074)
Other	0.115***	(0.036)	0.114**	(0.053)	0.145*	(0.080)
Country						
Germany	reference		reference		reference	
Spain	0.142**	(0.061)	-0.037	(0.074)	-0.127*	(0.073)
France	0.454***	(0.057)	0.091	(0.073)	0.225***	(0.063)
Italy	0.410***	(0.061)	0.259***	(0.078)	0.045	(0.064)
Firm size (number of employees)						
10-19	reference		reference		reference	
20-49	0.058	(0.041)	0.133***	(0.046)	0.07	(0.056)
50-99	0.189***	(0.044)	0.28***	(0.055)	0.181**	(0.071)
100-249	0.185***	(0.064)	0.365***	(0.058)	0.206***	(0.076)
250-499	0.093	(0.074)	0.357***	(0.073)	0.273***	(0.076)
500-999	0.066	(0.103)	0.54***	(0.075)	0.543***	(0.097)
≥1000	0.153	(0.115)	0.659***	(0.083)	0.508***	(0.081)
3-digit NACE	included		included		included	
Constant	11.138***	(0.079)	11.855***	(0.119)	11.032***	(0.105)
R^2	0.496		0.273		0.297	
Number of observations	3333		2111		1066	

Notes: Standard errors are bootstrapped (b. S. E.). Levels of significance are ***1%, **5%, *10%.

Robustness Checks

In the following we discuss the results of various robustness checks, which show that our conclusions do not change with alternative model specifications or alternative sampling procedures. For brevity, we report only the output elasticity of innovation in Table 5. In model 1 we rely on the predicted R&D intensity as the sole instrumental variable for innovation output in the knowledge production function. Then, we can use the cooperation variables as additional

[3]Hashi and Stojčić (2013), and Tevdovski, Tosevska-Trpcevska, and Disoska (2017) find marginal effects of innovation on labor productivity higher than 100% in some cases.

instruments in the Heckman model (for examples of studies that use the cooperation variables in the Heckman model see Acosta, Coronado, and Romero 2015; Griffith et al. 2006; Tevdovski, Tosevska-Trpcevska, and Disoska 2017). Model 2 estimates the knowledge production function and the productivity equation only for the subsample of innovative firms (R&D expenditures greater than zero) and incorporates the Mill's ratio as an explaining variable in these model stages to encounter possible selection bias. In model 3 the smallest (fewer than 20 employees) and the largest (more than 499 employees) firms are omitted from the regressions to account for possible large heterogeneity between firms of different sizes. In model 4 and model 5 we employ alternative product innovation indicators to address the possible concern that products "new to the firm" do not necessarily quantify "true" innovations or the success of new products. For model 4 this is the binary information whether the firm introduced a product that was new to the market and for model 5 it is the share of turnover attributed to these products new to the market. In model 6 and model 7 we excluded Spain or Italy respectively from the estimation to account for possible technology differences in these countries. The estimation of model 8 accounts for the differences in observation count by applying sampling weights based on the observation count by country.

Table 5: Overview of Estimated Output Elasticity of Innovation with Alternative Model Specifications

No	Description	Food	Chemicals and Pharma	Computer, electronic and optical products
1	Incorporating cooperation variables in both equations of the Heckman model	0.445*** (0.125)	-0.166 (0.117)	-0.122 (0.147)
2	Estimation of last two stages of CDM model only for innovative sample, using Mill's ratio	-0.051 (0.254)	-0.046 (0.222)	-0.297 (0.413)
3	Estimation only for medium sized firms	0.535*** (0.125)	-0.245* (0.128)	-0.026 (0.137)
4	Alternative product innovation indicator: introduced a product new to the market	0.364*** (0.105)	-0.253** (0.113)	-0.023 (0.129)
5	Alternative product innovation indicator: turnover share of new products	0.006*** (0.002)	-0.005** (0.002)	-0.001 (0.002)
6	Without Spain	0.119 (0.143)	-0.257* (0.138)	0.016 (0.124)
7	Without Italy	0.397*** (0.103)	-0.113 (0.133)	-0.086 (0.128)
8	Using country weights	0.252** (0.103)	-0.290** (0.129)	-0.010 (0.124)

In summary, the impression we have from our original model persists. In most cases, we find positive and significant output elasticity of innovation for food firms. In the two high-tech sectors we find in almost all estimations negative signs for innovation output, in the case of the chemicals and pharmaceuticals subsector even statistically significant in some estimations.

Discussion

We can see from the descriptive statistics in the appendix that a larger share of firms in the high-tech sector introduce a product innovation compared to firms in the food sector. Still, a considerable share of high-tech firms (up to 50 %) did not introduce any product innovations. One would suspect that as a consequence these firms perform worse than their innovative counterparts, especially in their innovation-focused environment. Contrary to our expectations, our results show that the positive effect of innovation output on labor productivity seems to be stronger in the food sector. We can only speculate about the possible reasons for this result.

First, one has to consider differences in the innovation process in the examined subsectors. The differences might be most striking in the case of product innovations. While food manufacturers can comparably easily launch new products by changing flavors or new compositions of products, newly developed products by chemicals and pharmaceuticals manufacturers are the result of extensive R&D and additionally lengthy approval processes. Accordingly, the R&D costs per new product are much higher for these firms. Higher R&D costs per new product can be also expected in case of the electronics sector. As a consequence, to be profitable, high-tech products need a much more prolonged life span in comparison to food products. In other words, high-tech companies possibly profit to a greater extent from product innovations in earlier years and might be classified as innovative even without any new product introductions during the three-year period covered by the CIS dataset. For these reasons, the link between current labor productivity and product introductions might be less straightforward in the high-tech subsectors.

Another explanation that we offer relates to the econometric strategy. Innovation in the productivity equation is prone to a variety of sources of endogeneity, not only by simultaneity but also omitted variables like the business strategy (e. g. brand focus contrary to a focus on mass products in the food sector) that affect the level of innovation efforts and labor productivity alike. Although in all estimation stages possible endogeneity is taken into account, the CDM methodology relies on the abundance of valid instruments in the CIS dataset. We acknowledge that the exogeneity of the used instruments is debatable. With the robustness checks we could, however, show that the results are robust to various modifications to the instrumental variable setup. To build up some intuition about the relationship between labor productivity and product as well as process innovation output we report in Table 6 results from OLS regressions.

Table 6: OLS Results for Returns to Innovation and R&D

	Food		Chemicals and Pharma		Computer, electronic and optical products	
	Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Product innovation	0.190***	(0.032)	0.071**	(0.035)	0.178***	(0.046)
Process innovation	0.262***	(0.030)	-0.017	(0.034)	0.008	(0.039)

Note: Shown are the results of two separate estimations for each sector of the regression of logarithm of labor productivity on the product or process innovation dummy and additional control variables (firm size, NACE 3-digit identifiers, and country dummies). Standard errors (S. E.) are robust.

These coefficients are possibly biased, but keeping in mind our insecurity about the quality of our instruments and that we are not sure how serious the correlation of the regressors with the error is, they serve as a useful benchmark to the endogeneity-robust instrumental variable results. The differences between the sectors are not as distinct as in the CDM model. What we also see here, however, is that the coefficients are larger for the food sector than for the high-tech sectors.

Conclusions

Our study aimed at uncovering differences in the productivity effects of innovation in the food in contrast to the high-tech manufacturing sector which we suspected to be the cause of the observed differences in R&D intensity in these subsectors. The results indeed point out to major differences but do not confirm our expectations. While we find strong positive productivity effects of innovation output in the case of the food sector we find no statistically significant effects in the high-tech sectors. The reason for this finding is hardly explored with the cross-sectional structure of the CIS dataset since we believe that for a full picture of the innovativeness of firms, a longer period than three years has to be taken into account, especially in the high-tech sectors. More precise analyses are possibly enabled by the upcoming implementation of a panel structure in the CIS surveys.

Given the long-standing classification of manufacturing sectors into low-tech and high-tech subsectors based on observed R&D expenditure ratios, it is surprising that there are not more studies with the CIS dataset examining the impact of innovation activity on firm performance separately by sector. If also our study does not provide a clear justification for its results, it shows that between firms of different manufacturing subsectors there are differences in the innovation behavior and productivity effects of innovation that need to be explored.

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Appendix

Descriptive Statistics

Table 7: Descriptive Statistics

Sector	Food				Chemicals and Pharma				Computer, electronic and optical products			
Country	DE	ES	FR	IT	DE	ES	FR	IT	DE	ES	FR	IT
Observations	210	1,641	901	581	298	334	218	216	209	1,049	329	524
Turnover (thousand Euro)	162,232.1 (566,219.6)	38,387.5 (123,956.4)	82,996.9 (243,520.6)	72,180.0 (236,930.4)	159,859.5 (516,547.5)	9,439.2 (018,261.5)	113,269.3 (317,852.6)	53,884.8 (128,973.1)	614,818.8 (1,770,923.1)	50,579.4 (182,278.7)	233,139.9 (801,394.3)	131,309.9 (288,118.6)
Employees	413.3 (1,273.7)	107.9 (258.4)	178.0 (339.5)	154.7 (477.2)	507.0 (1,287.3)	56.7 (77.6)	356.9 (806.4)	233.6 (694.3)	1373.6 (3,868.7)	109.4 (197.9)	405.4 (805.2)	260.5 (401.3)
Turnover per employee (Euro)	209,486.8 (348,269.4)	312,363.1 (685,452.6)	329,488.5 (504,469.5)	370,007.1 (737,262.6)	186,246.4 (184,212.8)	141,712.4 (131,675.8)	267,892.8 (560,042.8)	209,048.5 (128,735.2)	431,971.4 (697,088.5)	368,254.6 (1,271,700.3)	423,034.4 (503,981.2)	493,724.3 (1,293,250.9)
R&D expenditures per employee	2,236.3 (6,154.3)	2,972.2 (13,517.9)	9,354.4 (47,469.0)	3,317.6 (9,395.1)	20,896.9 (39,234.0)	11,038.1 (17,646.7)	27,473.0 (60,624.9)	11,955.5 (15,415.2)	22,926.9 (30,078.0)	7,651.8 (17,010.7)	14,197.9 (18,569.1)	10,037.6 (18,732.0)
Product innovation	0.371	0.293	0.332	0.363	0.836	0.584	0.734	0.764	0.727	0.501	0.587	0.586
Public funding												
Local	0.044	0.087	0.137	0.295	0.312	0.192	0.276	0.330	0.220	0.102	0.145	0.170
National	0.079	0.147	0.102	0.125	0.784	0.302	0.465	0.247	0.575	0.214	0.245	0.160
EU	0.035	0.038	0.067	0.069	0.296	0.123	0.227	0.176	0.394	0.051	0.096	0.097
Markets												
Local	0.848	0.966	0.909	0.943	0.560	0.919	0.784	0.861	0.541	0.952	0.748	0.876
National	0.433	0.801	0.640	0.838	0.923	0.949	0.972	0.949	0.933	0.952	0.915	0.922
EU	0.295	0.576	0.499	0.670	0.862	0.772	0.849	0.907	0.885	0.850	0.881	0.884
Other	0.186	0.397	0.334	0.494	0.832	0.698	0.812	0.856	0.775	0.707	0.748	0.754
Foreign homeoffice	0.057	0.048	0.089	0.040	0.131	0.090	0.243	0.153	0.249	0.201	0.398	0.185
Enterprise group	0.243	0.285	0.467	0.387	0.443	0.311	0.661	0.736	0.670	0.462	0.793	0.782

Note: Where standard deviations in parentheses are not given, the values are means of dummy variables, i. e. the share of the attribute in the population.

Table 8: Descriptive Statistics (Continued)

Sector	Food				Chemicals and Pharma				Computer, electronic and optical products			
Country	DE	ES	FR	IT	DE	ES	FR	IT	DE	ES	FR	IT
Number of employees												
10-19	0.224	0.252	0.353	0.336	0.195	0.338	0.216	0.162	0.134	0.224	0.155	0.177
20-49	0.267	0.296	0.228	0.258	0.309	0.356	0.216	0.185	0.172	0.331	0.188	0.116
50-99	0.167	0.214	0.091	0.134	0.124	0.162	0.138	0.190	0.158	0.195	0.109	0.156
100-249	0.157	0.147	0.092	0.131	0.148	0.099	0.092	0.222	0.120	0.149	0.100	0.246
250-499	0.057	0.057	0.141	0.083	0.047	0.045	0.197	0.139	0.096	0.060	0.237	0.158
500-999	0.048	0.023	0.057	0.033	0.054	0.000	0.060	0.074	0.057	0.029	0.131	0.088
≥1000	0.081	0.011	0.039	0.026	0.124	0.000	0.083	0.028	0.263	0.012	0.079	0.057
Cooperation partners												
Other enterprise group members	0.024	0.068	0.128	0.021	0.087	0.117	0.330	0.176	0.139	0.128	0.304	0.155
Suppliers	0.019	0.087	0.127	0.050	0.104	0.162	0.317	0.190	0.124	0.107	0.240	0.103
Customers	0.019	0.048	0.054	0.017	0.195	0.177	0.266	0.088	0.129	0.104	0.164	0.078
Competitors	0.010	0.042	0.029	0.021	0.060	0.078	0.156	0.125	0.067	0.057	0.094	0.057
Consultants	0.010	0.063	0.100	0.059	0.097	0.081	0.266	0.259	0.077	0.100	0.246	0.164
Universities	0.019	0.079	0.080	0.065	0.339	0.159	0.321	0.278	0.282	0.142	0.243	0.216
Government/public or private research institutes	0.019	0.102	0.063	0.029	0.262	0.168	0.252	0.157	0.239	0.162	0.152	0.124

Variable Descriptions

Labor productivity: the company's total turnover per employee in 2014.

R&D intensity: the company's total R&D expenditures per employee in 2014.

Public funding: dummy variables indicating whether the company received public funding from government institutions on the local, national, or EU level.

Enterprise group: dummy variable indicating that the company belongs to an enterprise group.

Foreign homeoffice: dummy variable indicating that its head office is located outside the country.

Markets: dummy variables indicating whether the firm sells its products in local, national, EU, or markets outside the EU.

Cooperation partners: dummy variables indicating cooperation with various innovation partners. The dummy variables assume the value one if the company cooperated with any partner of the respective group, irrespective of the partner's nationality.