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ABSTRACT

Firm Size and Innovation in the Service Sector

A rich literature links knowledge inputs with innovative outputs. However, most of what is known is restricted to manufacturing. This paper analyzes whether the three aspects involving innovative activity - R&D; innovative output; and productivity - hold for knowledge intensive services. Combining the models of Crepon et al. (1998) and of Ackerberg et al. (2015), allows for causal interpretation of the relationship between innovation output and labor productivity. We find that knowledge intensive services benefit from innovation activities in the sense that these activities causally increase their labor productivity. Moreover, the firm size advantage found for manufacturing in previous studies nearly disappears for knowledge intensive services.

JEL Classification: L25, L60, L80, O31, O33

Keywords: MSMEs, R&D, service sector, innovation, productivity, entrepreneurship

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1. Introduction

A robust literature confirms that firm size is a significant factor for the decision to invest in R&D and for subsequent innovation output (see, *inter alia*, Czarnitzki and Hottenrott 2011, Hall, Lotti and Mairesse 2009, Baumann and Kritikos 2016). Yet, the existing research into how R&D-investments affect firm innovative performance and, ultimately, firm productivity mostly concentrates on the manufacturing sector or does not differentiate among sectors. Empirical research on the innovative activities of firms in the service sector has only recently started.[1] Given the shift toward services in highly developed economies, as reflected by much higher start-up rates[2], it is increasingly important to better understand whether and, if so, how firms in knowledge intensive services (KIS), are able to engage in and benefit from innovative activities, as such firms have the largest innovation potential in the very heterogeneous service sector.

There are not only similarities but also differences between firms in KIS-industries and manufacturing that may affect innovation processes, such as different capital requirements for starting a business, different labor and qualification requirements, the physical production location, and the tangibility of output. This influences the industry-specific minimum efficient firm size. Consequently, while in the manufacturing sector the majority of individuals is employed in large firms, the opposite is true for knowledge intensive services. Obvious questions arise. Given that a strong and positive relationship between firm size and the probability of engaging in innovation activities is consistently found in manufacturing, does the large share of micro firms in knowledge intensive services mean that the great majority of these firms abstain from innovation?

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1 See, *inter alia*, Lööf and Heshmati (2006), Mairesse and Robin (2010), Musolesi and Huiban (2010).

2 For instance, in Germany there are around two start-ups per 10,000 employees in the manufacturing sector, of which only about every fourth (i.e. 0.5 per 10,000 employees) is considered to have the potential to innovate. By contrast, the number of new businesses in the knowledge intensive services is significantly higher. Since 1998, annually, an average of 5.6 start-ups per 10,000 employees are founded in the KIS industries (see Konon, Fritsch and Kritikos 2018).

Therefore, this study addresses three research questions: First, to what extent do firms that offer knowledge intensive services conduct R&D activities in order to become more innovative. Second, does the link between innovation input, innovation output, and productivity work in this part of the service sector in a similar way to manufacturing. Due to the paucity of compelling studies investigating whether small scale imposes a burden in terms of potential threshold levels for success of R&D investments, the third question is to what extent firm size matters in the service sector with respect to the decision to invest in new knowledge?

For our analysis, we use the IAB-establishment panel, which is a representative annual German survey of micro-, small-, and medium-sized firms that offers information on all industries in all firm size classes. Subjecting these data to systematic analysis enables us to contribute to the existing literature in three important ways: First, we provide empirical evidence on the triad relationship between innovation input, innovation output, and productivity in the KIS part of the service sector, also in comparison to manufacturing. Second, we differentiate between firm size, focusing on those firms in the KIS industries where the majority of employees work, i.e. the micro firms, and investigate whether the positive relationship between firm size and innovation probability also holds for KIS industries. Finally, we explicitly take the timing of the innovation process into account. While many previous studies rely on cross-sectional data and assume simultaneity between innovation inputs, their output, and productivity (see Hall 2011), we are able to exploit the panel structure of our data. More importantly, we extend the structural model of Crepon et al. (1998) by incorporating the structural model developed by Ackerberg et al. (2015) at the third stage of the innovation process. Therefore, this study is of high relevance to the literature, as our analysis contributes to the discussion of a causal relationship between innovation output and firm productivity.

We find that knowledge intensive service firms of all size classes are able to turn innovative input into innovation output. We further show that this newly produced knowledge causally leads to higher labor productivity, and that both findings thus hold for KIS firms in a similar way to manufacturing. However, the role of firm size is disparate across industry sectors: While larger firm size bestows advantages for innovation and productivity in manufacturing, our findings suggest that small firms in knowledge intensive services are less burdened by an inherent size disadvantage.

The rest of the paper is organized as follows. In Section 2, we review the empirical findings on the link between R&D inputs and innovative outputs, before explaining and documenting the relevance of KIS industries in the economy. We then make some theoretical considerations on how and why decisions to engage in R&D, as well as the ensuing innovative output, may differ between manufacturing and knowledge intensive services. Data and summary statistics are reported in the third section. Section 4 outlines the estimation strategy. The empirical results, robustness checks and the discussion of limitations are presented in section 5. A summary and conclusions are provided in the final section of the paper.

2. The Service Sector and the Relationships between R&D, Innovation, and Productivity

2.1. Previous Research

Firms engage in R&D activities in order to upgrade the quality of their products, increase sales, or reduce production costs, ultimately fueling productivity increases. In economics, the most prevalent approach to analyzing innovation at the firm level traces back to Griliches (1979), who introduces an augmented Cobb-Douglas production function that explicitly includes knowledge as an input, along with capital and labor, and links it to productivity. This framework describes the process from investment in research to productivity growth using past and present R&D expenditures to approximate the state of technical knowledge and to estimate its effect on productivity. A vast empirical literature follows this concept, confirming the validity of the knowledge production function and showing that R&D investment is positively related to firm productivity (see surveys by Mairesse and Sassenou 1991, Griliches 1998, Griffith, et al., 2004 Hall, et al., 2010).

Crepon, et al. (1998) introduced a structural equation model (the “CDM model”) that connects the approach of Griliches (1979) with a knowledge production function similar to Pakes and Griliches (1984)[3]. The model, which relates R&D effort to its determinants, includes an innovation equation that links R&D effort to innovation output, as well as a productivity equation that links innovation output to productivity. The framework proposed by Crepon et al. (1998) has become the workhorse model for empirical analyses and is used to examine the elasticity of productivity to R&D investment through innovation at the firm level, for instance by harnessing data collected as part of the Community Innovation Surveys (CIS).[4]

A large literature takes advantage of the CDM model, or modified versions of it, to examine these links at the firm level (see Mairesse and Mohnen 2010, Hall 2011 as well as Mohnen and Hall 2013 for surveys of the empirical literature). Due to data availability, most of these studies are cross-sectional and based on the assumption that there is simultaneity between innovation input, innovation output, and productivity. They usually approximate innovation input using R&D expenditures and find that the likeliness of having innovative output increases as R&D intensity grows, even though the estimated elasticities vary.[5] At the same time, there are not only firms that do not report successful innovations, although investing in R&D, but also businesses reporting innovation output despite lacking formal R&D spending. At the third stage, empirical research typically

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[3] Pakes and Griliches (1984) introduce a knowledge production function and show that firm’s R&D efforts increase the level of technological knowledge.

[4] The CIS collect firm level data on the innovativeness of European enterprises, and use standardized approaches to data collection as specified in the Oslo Manual (OECD/Eurostat 2005).

[5] For a recent overview and new evidence, see Kancs and Siliverstovs (2016).

finds innovation output to be positively correlated with labor productivity (see Mairesse and Mohnen 2010, Hall 2011, Mohnen and Hall 2013).

Panel data are increasingly employed (e.g. Hall, Lotti and Mairessee 2013, Siedschlag and Zhang 2015, Czarnitzki and Delanote 2017, Hall and Sena 2017) and some studies are taking dynamic feedback effects into account (Huergo and Jaumandreu 2004, Raymond, et al. 2015, Baum, et al. 2017). Few studies using the CDM model and its variations have examined whether there is a causal relationship from innovation to productivity, rather than a mere correlation. Raymond, et al. (2015) account for lags and feedback effects, and find such a unidirectional link in unbalanced panels of manufacturing firms from three CIS waves in France and the Netherlands. Hall and Sena (2017) mitigate the issue of endogeneity in the productivity equation by explaining productivity with innovation output variables of the preceding year, but do not consider possible persistence in productivity using feedback effects. Di Ubaldo and Siedschlag (2017) link three waves of the Irish CIS with two further micro data sets for the years 2005 to 2012 and explain productivity based on observations for the previous year.

Peters, Roberts, Vuong and Fryges (2017) analyze the relationships between research, innovation, and productivity using a dynamic structural model of a firm’s decision to engage in R&D that is contingent on R&D expenditure and prospective payoff. They consider that R&D costs are, for the most part, sunk and incurred up front, while a potential payoff may be delayed and subject to uncertainty. Peters, Roberts and Vuong (2017) extend this approach to investigate the influence of a firm’s financial fitness on the links between R&D, innovation, and productivity as well as profits.

Parallel to this, CDM-studies started taking heterogeneity into account, e.g. by separately analyzing subsamples they distinguish between aspects like firm size (Baumann and Kritikos 2016), sector (Siedschlag und Zhang 2015), sector and firm size (Hall and Sena 2017), technological intensity (Hall, Lotti and Mairesse 2009), as well as sector, and technological or knowledge intensity (Baum, et al. 2017). Hall, Lotti and Mairesse (2009) and Baumann and Kritikos (2016) explicitly examine the relationships between R&D, innovation, and productivity in SMEs in the manufacturing sector, the latter being the first on micro firms. Both studies find that SMEs produce substantial innovation output and that some firms do so without formal R&D investments. Further, their estimates show that firm size is positively associated with a firm's ability to produce innovation output. Moreover, in line with previous studies for larger firms, they find that R&D intensity has a significantly positive influence on the likelihood of having innovation and that micro and small firms in the manufacturing sector are able to turn innovation output into higher productivity.

The majority of research on the relationship between R&D, innovation, and productivity is confined to manufacturing firms (see e.g. Mohnen and Hall 2013). Notable studies further analyzing the service sector separately from the manufacturing sector in developed economies include Lööf and Heshmati (2006), who follow the concept of the CDM model, but use a modified implementation that only partially connects the steps of the model. The four equations in their model are estimated via an instrumental variable approach, using data from Sweden for the 1996 to 1998 period. They include a feedback effect from firm performance to innovation output and lagged firm performance in the growth version of their model. For the two sectors, they find homogeneity in the key elasticities between innovation input and innovation output as well as innovation output and productivity.

Mairesse and Robin (2010), relying on French CIS data from 1998 to 2000 and 2002 to 2004,[6] employ a CDM model that distinguishes between product and process innovation. They estimate the five equations of their model simultaneously, but separate

6 Service firms are only observed over the 2002 to 2004 period.

for the manufacturing sector in CIS3 and CIS4 as well as the services sector in CIS4. They find similar results for each of the two sectors: primarily product innovation raises labor productivity, while process innovation has an insignificant or marginal influence.

Musolesi and Huiban (2010) employ French data on 416 firms in the knowledge intensive business service sector (which covers a large part of KIS industries) from the 1998-2000 period and estimate a two-equation model with an innovation and a production equation.[7] Their results show that firms in knowledge intensive business services are able to produce innovation outcomes and that product innovation increases labor productivity (while process as well as non-technological innovation does not); both results are similar to those for firms in the manufacturing sector.

Using Dutch CIS data from the 2002, 2004 and 2006 surveys, enriched with data on ICT and tangible investment, Polder et al. (2010) analyze the effect of innovation on labor productivity in manufacturing and services by means of a CDM model. Their results show that ICT investment boosts innovation, being more relevant to services than manufacturing, while R&D has no effect on innovation output in service firms.

Also using CIS data, Segarra-Blasco (2010) estimate a variant of the CDM model that considers product, process, organizational innovation and patent applications as dichotomous variables. The study finds heterogeneity between manufacturing and service firms, as well as between low- and high-tech firms in both sectors. Most notably, small and young KIS firms, especially those in the high-tech sector, are inclined to carry out R&D, intensively invest in innovation and are involved in product, process, organizational and marketing innovation.

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[7] Musolesi and Huiban (2010) also show that firms from the knowledge intensive services producing intangible goods, use the same inputs for producing innovation output as manufacturing firms. This is why, when it comes to the analysis of innovative activities, the same conceptual framework (i.e. the knowledge production function of Grilliches, 1979) should be applied for these firms as for manufacturing firms.

Peters et al. (2018) estimate an augmented CDM model using CIS data on the service sector in Germany, Ireland, and the United Kingdom, covering the 2006 to 2008 period and including firms with at least 10 employees. Measuring innovation input in terms of innovation investment instead of R&D investment and considering product, process, organizational, and marketing innovation output, they find that innovation in the service sector is associated with higher productivity and that, in contrast to Musolesi and Huiban (2010), marketing innovation has the strongest link to productivity.

However, all six studies face data limitations. They lack information on a number of aspects, such as firms with fewer than 10 employees (or in case of Lööf and Heshmati (2006), Mairesse and Robin (2010), as well as Musolesi and Huiban (2010) on fewer than 20 employees), i.e. the huge number of micro firms in this sector. They also lack information on material, on high-skilled employees (with the exception of Lööf and Heshmati (2006), and Segarra-Blasco (2010)), and in the case of Peters et al. (2018) on capital. Moreover, all studies of the service sector (except of Lööf and Heshmati 2006), like most CDM studies on manufacturing, are cross-sectional, and are only able to make statements about correlation, but not causation between innovation and productivity.

2.2. The Role of Knowledge Intensive Services in the German Economy

The knowledge intensive service firms, consisting of firms in the two industries of "ICT" and "scientific and technical services," comprise an important part of the German economy. In 2014, these two parts of the service sector covered 23 percent of all establishments in Germany, contributing 17 percent to the German gross value added and accounting for 13 percent of all employees. For comparison, 26 percent of all jobs were in the manufacturing sector, which contributed 34 percent to the nation's gross value added.[8]

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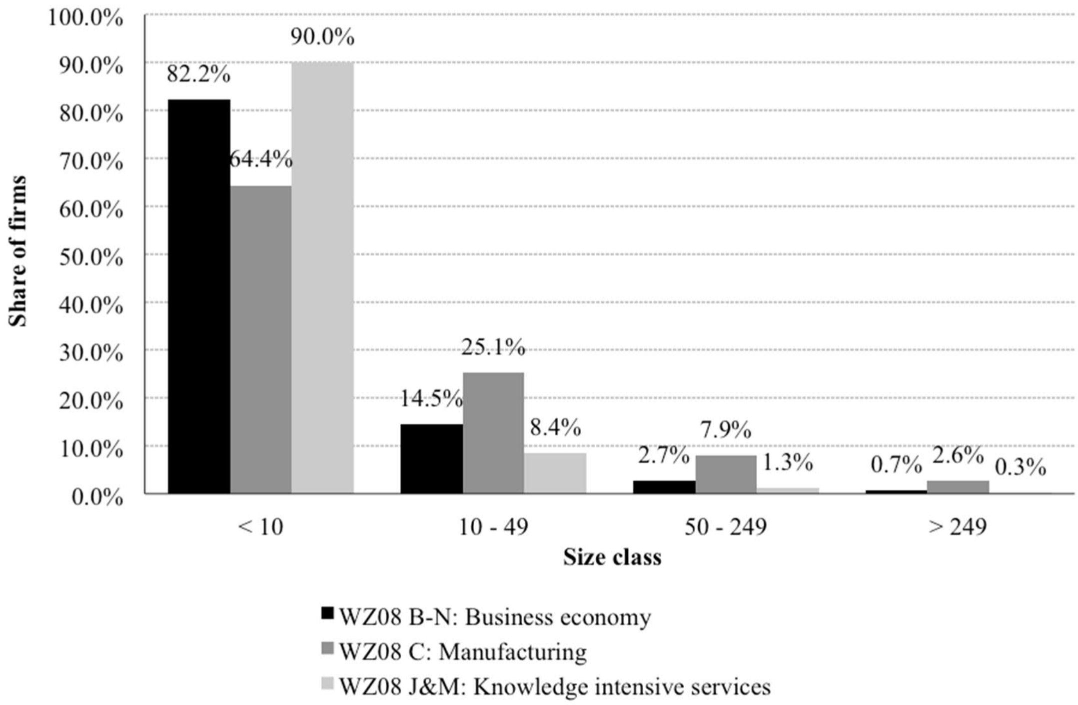
[8] These shares are based on own calculations of data provided by the Federal Statistical Office (2018).

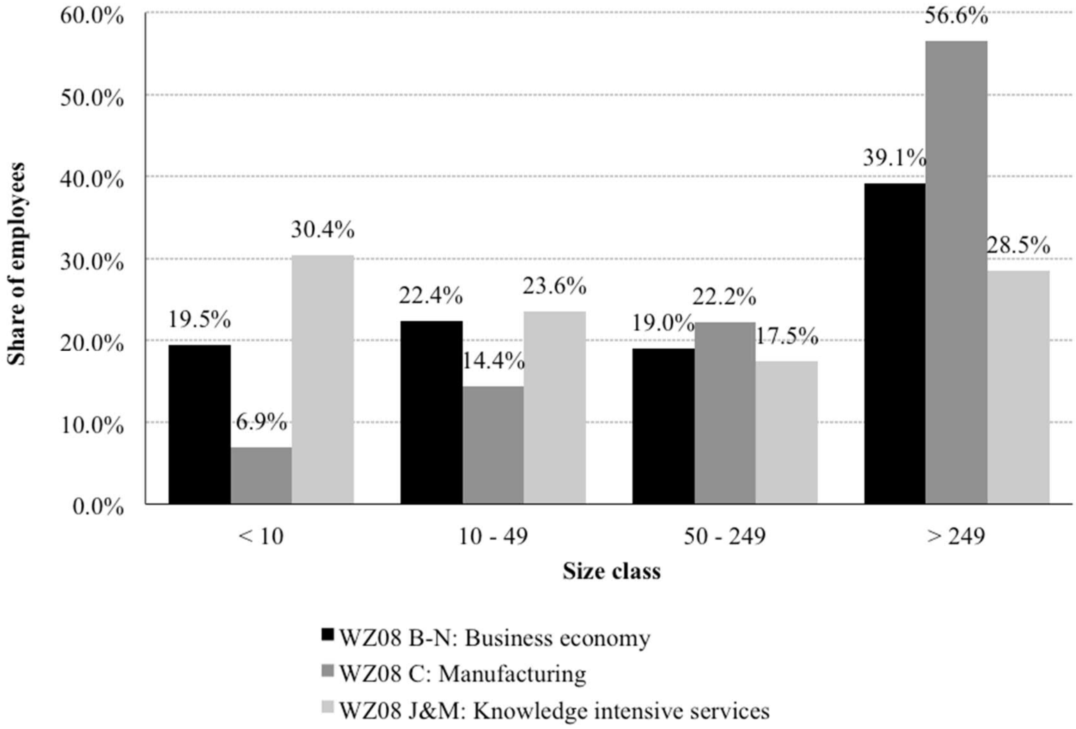
Figure 1: Share of Firms by Size Class and Economic Sector in Germany (2014)



Source: Federal Statistical Office Germany (2018); own calculation and representation.

Figure 1 illustrates that the preponderance of firms having fewer than 250 employees, for which Germany is famous, holds even more so for knowledge intensive services: 90 percent of all firms are micro firms, having fewer than 10 employees while in manufacturing only 64 percent are micro firms. The importance of these micro firms, in terms of employment, is shown in Figure 2. While the majority of employees work for firms with at least 250 employees in manufacturing, the opposite is true for the knowledge intensive services. In KIS, the highest share of individuals – just over 30% – work for a firm with fewer than 10 employees. These figures suggest that, on the one hand, a considerable and important part of the economy remains underexplored with respect to potential innovation activities and, on the other hand, that in terms of employment micro firms matter significantly more in the knowledge intensive services than in the manufacturing sector.

Figure 2: Share of Employees by Size Class and Economic Sector in Germany (2014)



Source: Federal Statistical Office Germany (2018); own calculation and representation.

2.3. Firm Size and Innovation Processes in the Service Sector

One commonality throughout the existing research that analyzes R&D, innovation, and productivity in the manufacturing sector is the key role played by firm size (Acs and Audretsch 1987, Acs, Audretsch and Feldman 1994, Cohen and Klepper 1996b). In terms of the decision to invest in R&D, there are compelling reasons suggesting that firm size will have a positive relationship to R&D investments. Theory revolves around the two conditions driving this decision: opportunity and appropriability.

In terms of opportunity, there are two reasons why access to investment funds for R&D tends to be limited for smaller firms. The first is that the lower level of profitability associated with small firms reduces the internal finance available for investing in R&D (Mairesse und Mohnen 2002). The second is that smaller firms are more informationally opaque for financial institutions than are larger firms, making it more difficult for providers of external finance to assess the quality of the projects proposed for funding

(Berger and Udell 2002). Therefore, smaller firms are more likely to face financial constraints when seeking external finance (Stiglitz and Weiss 1981, Czarnitzki and Hottenrott 2011).[9]

In terms of the second dimension, smaller firms are limited in their ability to appropriate the returns accruing from R&D investments, since the scale of their production and sales is inherently limited (Cohen and Klepper 1996b). This may particularly hold for firms that engage in R&D for the first time, due to sunk start-up costs (Peters, Roberts and Vuong, et al. 2017), explaining why investment opportunities in R&D are more limited in small companies relative to their larger counterparts. Robust and consistent empirical evidence finds a positive and significant relationship between firm size and R&D investment (Cohen and Klepper 1996a, Hall, Lotti and Mairesse 2009, Cohen 2010, Czarnitzki and Hottenrott 2011, Baumann and Kritikos 2016).

Since R&D is a key component in the knowledge production function, it would seemingly follow that small firms are burdened by an inherent innovation disadvantage. However, it is important to emphasize that most of the findings, and even theory, apply to manufacturing (Gallouj and Weinstein 1997). Considerably less is known about firms outside of manufacturing when it comes to the relationships between R&D, innovation, and productivity, and how these relationships are influenced by firm size.

Both the production and innovation processes are among KIS firms, to an extent, different from manufacturing in that they may affect a firm's R&D investment decision. Focusing on the production process per se, KIS firms generate more customized knowledge products than do manufacturing firms (see also Gallouj and Weinstein (1997)). Therefore, the role of scale economies in producing such intangible goods may

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9 Peters, Roberts and Vuong (2017) extend this discussion of how the availability of financial resources influences a firm's ability to invest in R&D. They argue that a poor financial status may deter businesses from engaging in R&D and find that R&D investments of firms with a sound capital base are more likely to yield innovation output. Their estimates show that the long-term returns to R&D increase with a firm's financial fitness.

be less relevant in the larger part of knowledge-intensive services (except for network-based services). Further, higher real capital requirements (e.g. in terms of machinery) may facilitate a larger scale of output which in turn is more conducive to innovative activity and enhances productivity in manufacturing, where scale and efficiency are positively related. This may not necessarily hold for knowledge intensive services in the same way, as there are lower capital requirements. Hence, in most parts of knowledge intensive services, firm size may not play the same role in influencing decisions about R&D investment as it does in manufacturing.[10]

There are to some extent also differences between firms in KIS-industries and manufacturing that are directly related to innovation processes (see e.g. Forsman 2011). First, the process of creating innovative products is different in KIS industries. Because capital requirements are generally lower among KIS firms than in manufacturing, producing innovative products or developing new processes that improve the delivery of products also tend to be less capital intensive, and therefore requires relatively low investments (see also Table 1). Similarly, it is also less resource intensive in terms of the R&D work force, and there might be no need for a physical production site to produce a new service product or to implement a new production process.

A further issue relates to the question of the extent to which formal R&D-investments in the service sector produce new knowledge in the same way it does in manufacturing. First of all, we observe that, in knowledge intensive services, the majority of R&D expenditures (75%) are used to finance R&D workers (Stifterverband 2017), clarifying that R&D spending is mainly invested into highly educated "brains" and less into machines or equipment. Moreover, there is an ongoing discussion to what extent

[10] This is not to say that there are no firm size advantages in terms of economies of scale and economies of scope. However, these advantages seem to be smaller among KIS firms when compared to manufacturing.

innovation output is produced without formal investment into R&D. Empirical research shows that even in manufacturing a certain share of firms produce innovative output without a formal R&D budget. This issue of formality might be more important in the context of knowledge intensive services. Individuals producing knowledge on a daily base may directly observe opportunities for innovation and, thus, are more frequently able to contribute to the generation of new knowledge during their routine work, even in the absence of formal R&D spending in the classical sense (de Jong and Marsili 2006).

Overall, these considerations make clear that not only should the minimum efficient firm size in KIS industries be smaller than in manufacturing, but also that both opportunity and appropriability may influence R&D decisions in KIS firms differently from manufacturing. There might be lower threshold levels and reduced financial constraints, allowing us to posit that differences in firm size should be less important in the decision to engage in innovative activities.

Based on these considerations, we analyze the following research questions: First, we aim to reveal to what extent firms offering knowledge intensive services are investing in R&D to become more innovative. We also aim to find out to what extent do KIS firms generate innovation output without formal R&D. Second and more crucially, we causally examine whether the link between innovation and productivity works in this part of the service sector similar to the manufacturing sector, i.e. whether the ability to innovate affects firm productivity. Third, we investigate in two ways the extent to which firm size is a burden in the service sector, namely when the decision is made to engage in innovation, and when firms aim at translating innovation input into output.

3. Data

This study uses the IAB Establishment Panel (IAB-EP), an annual survey of approximately 16,000 establishments with at least one employee liable to social security.

The establishments are drawn from the BA establishment file, which comprises roughly two million establishments that have notified the social security agencies of their employees, as stipulated by law. It is representative at the size class, industry-group and federal state levels. In addition to questions directly concerned with employment, the survey also inquires about business performance, investment, and R&D engagement.[11] Using dichotomous variables, as defined in the Oslo Manual (OECD/Eurostat 2005), the survey takes account of the introduction of new products and implementation of new processes that helped to improve the production process or the provision of services within the firm. However, it does not ask whether innovations are successful in terms of increased sales or reduced costs.

The IAB-EP covers micro firms across all industries, a distinct advantage over the other main German panel-surveys on innovation. The KfW SME panel (KfW Mittelstandspanel), for instance, concentrates on micro enterprises in manufacturing, while the Mannheimer Innovationspanel (MIP) does not capture firms with fewer than five employees (Maaß and Führmann 2012). The main disadvantage of the IAB-EP is that it considers establishments instead of firms. Yet, the overwhelming majority of MSME are single-establishment firms, which is why this disadvantage is a minor issue. Therefore, we will also speak of firms throughout the rest of the paper.

In line with the MSMEs definition of the European Commission (European Commission 2003), we restrict the sample to establishments with no more than 249 employees. We distinguish them by the number of employees, i.e. between micro (1-9 employees), small (10-49), and medium-sized establishments (50-249), and do not introduce further restrictions based on revenue. We retain sole proprietorship, partnerships, and private limited liability companies.[12] Moreover, we only include

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[11] See Fischer et al. (2009) for a detailed documentation of the data.
[12] Public corporations and other legal forms such as associations are not considered.

observations with complete information for all variables used in our estimates.[13] In our analysis, we concentrate on observations for establishments that are active in either the manufacturing industry or knowledge-intensive services (Gehrke, et al. 2013). The latter contains firms in the areas of information and communication, as well as in professional, scientific and technical activities. Establishments in the financial services and insurance sector are excluded.

Table 1: Descriptive statistics

	Manufacturing industry	Knowledge-intensive services				
	1-249	1-249	50-249	10-49	5-9	1-4
Sales (1,000 Euro)	8,408.40	1,906.82	12,704.28	2,185.38	480.62	202.78
Material (1,000 Euro)	5,135.94	738.17	5049.59	819.99	170.04	81.05
Investment (1,000 Euro)	443.36	98.89	481.15	104.87	23.47	17.18
Labor	47.14	17.37	93.94	23.15	6.59	2.55
Share of R&D engagement[a]	0.28	0.19	0.37	0.24	0.21	0.10
Share of innovators	0.58	0.48	0.73	0.57	0.47	0.36
Share of product innovators	0.55	0.46	0.72	0.55	0.45	0.35
Share of process innovators	0.21	0.18	0.41	0.23	0.15	0.10
Share of innovators without R&D[a]	0.33	0.32	0.41	0.35	0.30	0.29
Age class (0-5 years)	0.07	0.12	0.09	0.09	0.13	0.15
Age class (6-19 years)	0.38	0.49	0.42	0.41	0.47	0.57
Age class (≥ 20 years)	0.55	0.39	0.49	0.50	0.40	0.27
Share of high skilled employees	0.06	0.22	0.34	0.30	0.27	0.11
Part of firm-group	0.14	0.12	0.39	0.21	0.06	0.03
Main sales market export	0.09	0.03	0.11	/	/	0.02
High competitive pressure	0.43	0.32	0.34	0.33	0.33	0.30
Limited	0.71	0.49	0.89	0.69	0.51	0.24
Profitable	0.42	0.53	0.57	0.59	0.53	0.46
Training	0.58	0.65	0.91	0.85	0.67	0.43
Technical state of equipment	0.58	0.78	/	0.84	0.77	0.71
Observations	9,317.00	2,980.00	244.00	928.00	676.00	1,132.00

Notes: The table displays means for continuous variables and shares otherwise. (a) Based on observations in odd years; "\"Observations censored by the IAB for privacy reasons.
Source: IAB Establishment Panel Survey 2009-2014. Own calculations.

We have access to waves from 2009 to 2014. Note that the questionnaire of each wave addresses two different points in time. Questions regarding inputs and the economic

[13] Note that R&D activities are observed only in odd years. Yet, we do not drop missing observations on R&D in even years.

output, such as sales or innovation, refer to the previous year $(t-1)$. Labor related questions such as education of workers, but also the question regarding R&D refer to the current year (t). Therefore, we rearrange the data so that all variables refer to the same year. After the data cleaning the final sample consists of 12,297 observations in total, of which 9,317 belong to manufacturing industries and 2,980 are in the knowledge intensive services.[14] Consequently, and contrary to CIS data, we observe R&D and innovation in the same year and do not need to assume that firms continuously invest in R&D.[15]

Table 1 shows the descriptive statistics for those variables used in the analysis for both manufacturing and service firms, with the latter also separated by size classes. It reveals that KIS firms are considerably different from manufacturing firms. They have lower sales, make lower investments, use less material and intermediate inputs, and also employ less labor per firm. As the comparison with Table A.1 in the appendix shows, this also holds when we compare the two industries within size classes.

While 28 percent of all manufacturing units in the dataset report R&D engagement, only 19 percent of KIS firms do. In these services, the share of large SMEs (50-249 employees) engaging in R&D is almost 4 times higher than that of micro enterprises (1-4 employees). Moreover, in both sectors, manufacturing and services, another 30 percent of all firms report an innovation without stating a formal R&D engagement so that the overall innovator share is little less than 60 percent among manufacturing, while among all KIS firms nearly every second firm innovates. This differs between firm size classes, where 36 percent of the very micro firms in the KIS sector report a successful innovation, and 73 percent among medium sized firms. Interestingly, the share of firms stating an

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[14] The total number of observations before any cleaning is 33,164. Dropping the large firms reduces this number to 26,728. We further drop observation with missing data on sales, labor, and material, etc. This reduces the dataset to 19,513 observations. After the final rearrangement, we have 12,297 observations.

[15] CIS data observe R&D in t_0 while innovation is observed in $t_1$to t_{-3}.The usual assumption is, when using CIS data, the firms invest in R&D continuously.

innovation without formal R&D engagement is increasing in KIS industries from 29 percent among micro firms to 41 percent among medium-sized firms.

Nearly all service firms innovating report a product innovation. This share ranges from 35 to 72 percent between the smallest and medium sized KIS firms. Process innovation relating to the implementation of new processes that improved the service provision within the firm is reported less often, ranging between 10 percent for the very micro firms and 40 percent for the largest ones. In this context, we should also emphasize that in KIS industries a product often denotes a customized service process. Therefore, incremental product innovation and process innovation tend to be to a certain extent "synonymous" (Gallouj and Weinstein 1997, 542) which is why it is difficult to clearly differentiate between product and process innovations in the KIS industry.

Firms from the knowledge intensive services also differ with respect to the share of high skilled employees: at 22 percent, this share is significantly higher than in manufacturing. This is not only driven by SMEs. The share is at 11 percent for micro firms in KIS, but only at 2 percent for micro firms in manufacturing. Compared to manufacturing firms, the KIS firms further face lower competitive pressure, which matches with the observations that they are less active in international markets. The reduced competitive pressure also seems to lead to more companies in KIS than in manufacturing industries assessing their earnings situation as good. The share of service firms investing in the training of their employees is 65 percent, compared to 58 percent in manufacturing. In addition, almost 80 percent of firms in KIS report modern technical equipment, in contrast to less than 60 percent in manufacturing. This is in accord with the fact that investment cycles and necessary equipment are quite different between, for instance, a mechanical engineering firm and a consulting firm. Overall, Table 1 reveals that firms in the manufacturing and in the knowledge-intensive services differ quite strongly in several ways from each other.

4. Model

4.1. The CDM model

We start by briefly describing the CDM model (Crepon, Duguet and Mairesse 1998) in a variant proposed by Mairesse et al (2005). This variant uses occurrence rather than the intensity of R&D engagement and innovation output. Thus, the strict selectivity issue concerning R&D and innovation intensity does not arise, for which Crepon, Duguet and Mairesse (1998) had to correct for in their specification The model breaks down the innovative process between a firm's decision to invest in R&D and its productivity into three recursive steps. The first step uses a probit model to estimate the probability of engaging in R&D. The R&D decision (r_i^*) of firm i is modeled as:

(1) $$r_i = \begin{cases} 1, & if\ r_i^* = X_i'\alpha + e_i > \hat{c} \\ 0, & if\ r_i^* = X_i'\alpha + e_i \leq \hat{c}, \end{cases}$$

where r_i is the observed binary variable for R&D activities, r_i^* is an unobserved latent variable[16] that defines the probability of engaging in R&D, X_i' is a vector of determinants affecting firms' decision to undertake R&D investment and e_i is the error term. If the unobserved latent variable r_i^* is larger than a certain threshold level $\hat{c}$, the observed r_i will equal one and zero otherwise.

The second step models the "knowledge production" (Pakes and Griliches 1984), which is the transformation from innovation input to innovation output, as follows:

(2) $$i_i = \begin{cases} 1, & if\ i_i^* = r_i^*\beta + Z_i'\delta + u_i > \hat{c} \\ 0, & if\ i_i^* = r_i^*\beta + Z_i'\delta + u_i \leq \hat{c}, \end{cases}$$

where i_i is the observed binary variable for innovation (as mentioned in section 3 regardless whether it is a product or a process innovation), r_i^* is the latent R&D decision

[16] An asterisk denotes latent variables, while all other variables apart from the error terms are observed.

predicted in the first step,[17] Z_i' contains further determinants influencing the knowledge production, and u_i is the error term. The first two steps of the model are each estimated by means of a probit.

Using the predicted R&D decision from the first step takes into account that firms may engage in innovative effort without reporting R&D engagement, like the majority of micro firms.[18] It also helps to overcome the selectivity and endogeneity issue. Such an issue would arise if the innovative effort (r) and produced knowledge (i) were determined by the same unobservable firm characteristics. In such a case, r_i and u_i are (potentially positively) correlated and parameter β would be (upward) biased. Using the predicted probability as instrument instead of the observed R&D engagement variable avoids the potential endogeneity bias, assuming that X_i' and u_i are uncorrelated.

In its third step, the CDM model uses a productivity function that includes the predicted probability for innovation as a proxy of knowledge input. Using the predicted value seeks to alleviate the potential endogeneity issue with respect to innovation. The function to be estimated in the third stage is the Griliches (1979) production function, which is a plain Cobb-Douglas production function augmented by the knowledge stock. In case of the CDM, this stock is replaced by the results from the second stage of the CDM approach, hence, the predicted probability for innovating. Thus, the respective estimation equation in logs is

$$(3) \qquad y_i - l_i = \alpha_0 + \alpha_1' l_i + \alpha_2 k_i + \alpha_3 i_i^* + \overbrace{v_i}^{\omega_{it}+\varepsilon_{it}},$$

[17] This is in line with Griffith et al. (2006), Hall et al. (2009), and Baumann and Kritikos (2016), who similarly include the predicted R&D intensity as an explanatory variable in the knowledge production function. Griffith et al. (2006) argue that firms may report R&D effort only if it exceeds a certain threshold so that innovative effort, such as workers investing a small amount of their working time to improve the process they are performing, would not be reported. This is based on the assumption that the relationship between innovation input and output is the same for firms that report R&D activities and those that do not.

[18] This also allows for imputing values for observations with missing values on the R&D decision (see section 3).

y_i is gross value added, l_i is the labor input, hence $y_i - l_i$ is labor productivity, k_i is the capital input variable, i_i^* is the predicted probability for having innovation output, and ν_i is the observed error term.[19] Usually, additional control variables are also included in Eq. (3), such as time or sector dummies. However, consistently estimating Eq. (3) is not trivial, due to the unobserved total factor productivity. Researchers can directly estimate an intercept, which is the average total factor productivity of all firms under the production function. But even in such an estimation, nevertheless, the observed error ν_i contains not only the true error term that captures the true measurement errors ε_{it}, but it also contains the firm specific total factor productivity (ω_{it}).

Because TFP is unobserved and, therefore, part of the error term ν_i, estimations are subject to the simultaneity problem first emphasized by Marschak and Andrews (1944). Simply put, while TFP is unobserved by research, firms know, or at least have a vague idea, about their productivity, thus they will choose all inputs accordingly. Consequently, the inputs are correlated with the error term ν_i as it contains the firm specific part of TFP and, in turn, estimated coefficients are potentially biased. Hence, even the use of cross sectional data does not avoid the simultaneity problem.

The productivity literature has a long history of dealing with this issue.[20] One approach is the structural model of Ackerberg, Caves and Frazer (2015), which builds upon the seminal studies of Olley and Pakes (1996) and Levinsohn and Petrin (2003).

4.2. The ACF model

The ACF model aims to split the observed error term so that the unobserved firm specific factor productivity can be "observed", thus one can control for it in the estimations – these approaches are therefore referred to as control function approaches. Since

[19] $\alpha_1^{\prime}$ replaces $\alpha_1 - 1$ if labor productivity serves as dependent variable.

[20] We refer to Ackerberg et al. (2007) and Aguirregabiria (2009) for a comprehensive overview.

Levinsohn and Petrin (2003), control function approaches utilize the assumption that an intermediate input demand function with certain characteristics exists: $m_{it} = h_t(\cdot)$. *Inter alia*, it is assumed that such a function contains all observed variables relevant for material and TFP (ω_{it}), that the function is strictly monotonic in ω_{it}, and that TFP is the only unobserved state variable in that function (Ackerberg, Caves and Frazer 2015). Given these assumptions, the function $h_t(\cdot)$ is invertable, which allows for replacing the unobserved TFP with a function of observables in the production function. Using Eq. (3) as starting point, this leads to:

$$y_{it} = \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 m_{it} + \alpha_4 i_{it}^* + h_t^{-1}(l_{it}, k_{it}, m_{it}, i_{it}^*) + \varepsilon_{it} \quad \text{or,} \quad y_{it} = \varphi_t(l_{it}, k_{it}, m_{it}, i_{it}^*) + \varepsilon_{it} \tag{4}$$

where $\varphi_t(l_{it}, k_{it}, m_{it}, i_{it}^*) = \alpha_1 l_{it} + \alpha_2 k_{it} + \alpha_3 m_{it} + \alpha_4 i_{it}^* + h_t^{-1}(l_{it}, k_{it}, m_{it}, i_{it}^*)$. m_{it} has to enter if a sales production function is used. The function $h_t^{-1}(\cdot)$ is approximated by a polynomial as its functional form is unknown (Levinsohn and Petrin 2003).

Even when controlling for TFP, the coefficients are not identified when estimating Eq. (4), e.g. by means of OLS, because of the functional dependency between the regressors and $h_t^{-1}(\cdot)$, which also contains the regressors (see Ackerberg, Caves and Frazer 2015 for the proof). Nevertheless, estimating Eq. (4) dislodges the TFP from the error term ν_i, see Eq.(3), and is needed as the first stage in the two-stage ACF procedure.

The identification strategy in the second stage relies on the assumption that TFP follows a first-order Markov process (Olley and Pakes 1996, Levinsohn and Petrin 2003, Bond and Söderbom 2005, Ackerberg, et al. 2007, Ackerberg, Caves and Frazer 2015). Hence, the firm's productivity expectation is derived from its past experience, contained in the information set Υ_{it-1}, and a random productivity shock ξ_{it} in t that is independent of all past information. This model, formally $\omega_{it} = E(\omega_{it}|\Upsilon_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$, can be approximated by a polynomial in ω_{it-1} of order n. Following Petrin, Poi and Levinsohn (2004), we set $n = 3$, hence:

(5) $$\omega_{it} = \lambda_0 + \lambda_1 \omega_{it-1} + \lambda_2 \omega_{it-1}^2 + \lambda_3 \omega_{it-1}^3 + \epsilon_{it},$$

where ϵ_{it} is an error term that contains true measurement error and the unobserved productivity shock ξ_{it}. Given Eq. (4), we infer ω_{it} from rearranging that function: $\varphi_t(l_{it}, k_{it}, m_{it}, i_{it}^*) - \alpha_1 l_{it} - \alpha_2 k_{it} - \alpha_3 m_{it} - \alpha_4 i_{it}^* = h_t^{-1}(l_{it}, k_{it}, m_{it}, i_{it}^*)$ or $\omega_{it} = \hat{\varphi}_{it} - \alpha_1 l_{it} - \alpha_2 k_{it} - \alpha_3 m_{it} - \alpha_4 i_{it}^*$. This rearranged function is substituted into Eq. (5), which is then estimated by means of GMM using the $\hat{\varphi}_{it}$, as estimated in the first step, and starting values for the coefficients.[21]

Identification further relies on timing assumptions regarding the firms' decisions for the different inputs. Since the seminal study of Olley and Pakes (1996), it is assumed that the decision to invest is taken in $t-1$ but carried out in t, which is why investment in t is independent of the productivity shock ξ_{it}. Ackerberg, Caves and Frazer (2015) show that the labor variable is correlated with ξ_{it}. This holds even if labor is considered "less flexible" than material and when firms decide about labor before they decide about material, e.g. at $t-b$ with $0 < b < 1$. As also shown, the decision for l_{it-1} exploits only the information the firms possess at $t-1$, which are in information set Υ_{it-2}. Consequently, l_{it-1}, which was decided upon at $t-b-1$, is not correlated with the productivity shock in t. The same holds for the material variable. The use of the predicted innovation probability as an instrument for the observed innovation variable ensures orthogonality with ξ_{it}.

[21] Note that dummy variables for years, capturing cyclical effects, for legal form and for region, etc., are also included in the first step of the ACF procedure. The estimated $\hat{\varphi}_{it}$ is supposed to capture the error free output and should also be free of cyclical effects, etc., as these effects distort the input-output relationship as described by the production function. Thus, the predicted $\hat{\varphi}_{it}$ is corrected for cyclical and other structural effects.

4.3. Estimation strategy

Our estimation strategy reaps the benefits of both models. We analyze the relationship between R&D and innovation using the first two stages of the CDM model. This also allows us to overcome the data limitation that R&D is observed only every other year. While most studies ignore the simultaneity issue of the production function estimation in the third stage, we make use of the ACF model instead.

We solve the endogeneity issue in the ACF approach with respect to R&D by using the predicted probabilities to innovate from the second stage of the CDM model. By using CDM results in the ACF model, we solve the selectivity problem regarding innovating firms that we would face if only ACF is employed. Note that we conduct the full multi-stage procedure separately for each group of firms. Thus, we allow for different production functions per size class and industry-group. We consistently use bootstrapped standard errors after the first step of the estimation procedure.

With respect to the production of innovation, we partly differ from the existing empirical literature. Given the short discussion in section 3 according to which it is difficult to differentiate between product and process innovation in KIS industries, our output variable of interest in the main estimation approach at the second stage of the CDM Model will be the likelihood of being an innovator. Consequently, we will also use the predicted probability of being an innovator as explanatory variable at the final stage of our estimation approach. Thus, we will not separate between the effects for product and process innovation. These separate effects will then be estimated in the robustness checks. As of the control variables at the three stages, we follow the existing literature on the CDM model and control for variables that may also influence the knowledge production (for an extensive discussion see *inter alia* Hall and Sena, 2017).

5. Econometric Results

We run separate regressions for the sample of manufacturing and knowledge intensive service (KIS) firms, subsequently distinguishing the KIS firms between micro firms (less than 10 employees) and larger firms (with 10 to 249 employees). This allows us to investigate differences between sectors and size classes within the KIS sector.[22] In each of the following three sections, we first present findings with respect to the full samples of manufacturing and KIS firms before pointing to differences within the KIS sector.

5.1. First stage – innovative effort

Table 2 presents the estimation results of Eq. (1). The dependent variable takes on the value of one if the firm engages in R&D and zero otherwise. Columns 1 and 2 present the results for the full sample of manufacturing (column 1) and KIS-industries (column 2) where we employ dummies for firm size and firm age with large sized firms and mature firms (firms with an age above 20 years) being the reference group.

We observe a notable difference for the size class dummies in the estimations of the two samples. The negative effect of the size class dummies is always significant in the manufacturing sample, indicating that firm size is positively related with the decision to start an R&D engagement, while it is almost never significant for KIS firms, with the exception of the very small firms with 1-4 employees. Given that marginal effects are considerably smaller among KIS firms, we can exclude that the insignificance results from a smaller sample size in this sector. This points to an important effect: there is a significant difference in R&D decisions between the two industries in that firm size is less relevant in services.

[22] Here, we do not discuss the outcomes for manufacturing differentiated for firm size classes any further, as this is beyond the scope of the present paper. A more detailed discussion is found in Baumann and Kritikos (2016).

Moreover, there is also an interesting age class effect with respect to KIS firms. While in manufacturing, young and mature firms start with similar probabilities R&D activities, young firms in KIS industries have a higher likelihood of engaging in R&D than firms that are for 20 years or more in the market.

Table 2: R&D engagement

	Manufacturing		Knowledge-intensive services					
	1-249		1-249		10-249		1-9	
	α/s.e.	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx
1-4 employees	-1.333**	-0.344	-0.403*	-0.092			-0.315	-0.060
	(0.13)		(0.18)				(0.13)	
5-9 employees	-1.265**	-0.326	-0.110	-0.025				
	(0.10)		(0.17)					
10-49 employees	-0.547**	-0.141	-0.105	-0.024	-0.100	-0.029		
	(0.06)		(0.16)		(0.16)			
Age class	-0.010	-0.003	0.304*	0.070	0.355	0.102	0.287	0.055
(0-5 years)	(0.10)		(0.15)		(0.23)		(0.19)	
Age class	0.130*	0.033	0.348**	0.080	0.303*	0.087	0.376*	0.072
(6-19 years)	(0.06)		(0.11)		(0.14)		(0.16)	
Group	0.051	0.013	0.217	0.050	0.212	0.061	0.196	0.037
	(0.07)		(0.14)		(0.15)		(0.29)	
Main market export	0.819**	0.211	0.844**	0.193	0.847**	0.243	0.831*	0.158
	(0.09)		(0.23)		(0.30)		(0.35)	
Competitive	0.015	0.004	-0.047	-0.011	0.008	0.002	-0.099	-0.019
pressure	(0.05)		(0.09)		(0.14)		(0.13)	
Limited	0.570**	0.147	0.744**	0.171	0.912**	0.262	0.685**	0.130
	(0.09)		(0.12)		(0.19)		(0.14)	
Profitable	0.024	0.006	-0.014	-0.003	-0.088	-0.025	0.061	0.012
	(0.05)		(0.08)		(0.12)		(0.11)	
Industry, Region, Year	Yes		Yes		Yes		Yes	
N	5,394		1,735		681		1,054	
Log likelihood	-2,464.46		-716.15		-346.89		-366.36	
Pseudo R2	0.224		0.149		0.120		0.140	

Note: Clustered s.e. at the firm level in parentheses. Reference groups: medium-sized firms, age class ≥20 years, *Significance at $p < .05$ level,**Significance at $p < .01$ level.

We observe several similarities between the two industries. First, the positive and statistically significant coefficient of internationalization suggests that having an international orientation is associated with a higher propensity to engage in R&D. This holds across all firm sizes in the sample, with the positive effect of exporting being more pronounced in the SME subsample of KIS firms compared to their smaller counterparts. Second, a positive and statistically significant relationship is also found to exist between firms with a limited liability structure and the likelihood of R&D engagement. This variable may capture aspects such as a firm's creditworthiness.

Beyond these, no other observed variables unfold significant effects on the probability of engaging in R&D, be it the variable indicating group affiliation, strong competition or a good profit situation. The lack of a significant effect of a positive profit situation is worth being highlighted; it may be interpreted in the sense that firms make R&D efforts due to strategic decisions. Overall, while the rest of variables are found to be quite similar between the two industries, the near absence of a firm size effect in influencing R&D engagement of firms in knowledge-intensive services is striking.

5.2. Second stage – knowledge production

Table 3 provides results for the second stage of the model, which estimates the likelihood of a firm being an innovator (the knowledge production function, Eq. (2)), i.e. having introduced a product or a process innovation. Here the predicted values of R&D engagement from the first step are used to correct for endogeneity. In order to take into account that we use the predicted probabilities of the R&D variables, we compute bootstrapped standard errors with 100 replications.[23] To do so, the two probit models for R&D engagement and innovation output are estimated sequentially on 100 random samples drawn from the data with replacement.

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[23] We implement the bootstrap, as potential bias introduced by using a predicted value should converge toward zero in very large samples.

Table 3: Knowledge production function

	Manufacturing		Knowledge-intensive services					
	1-249		1-249		10-249		1-9	
	α/s.e.	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx
1-4 employees	-0.500**	-0.172	-0.364*	-0.126			-0.029	-0.010
	(0.10)		(0.19)				(0.10)	0.00
5-9 employees	-0.425**	-0.147	-0.321	-0.111				
	(0.09)		(0.17)					
10-49 employees	-0.168*	-0.058	-0.176	-0.061	-0.143	-0.049		
	(0.07)		(0.16)		(0.17)			
Age class	0.082	0.028	0.341**	0.118	0.125	0.043	0.419**	0.145
(0-5 years)	(0.07)		(0.11)		(0.19)		(0.16)	
Age class	-0.010	-0.003	0.081	0.028	0.050	0.017	0.091	0.031
(6-19 years)	(0.04)		(0.08)		(0.14)		(0.12)	
Share high qual. empl.	1.556**	0.537	0.558**	0.194	0.223	0.076	0.830**	0.287
	(0.22)		(0.14)		(0.26)		(0.18)	
Training	0.322**	0.111	0.174*	0.060	0.037	0.012	0.221**	0.076
	(0.04)		(0.07)		(0.14)		(0.08)	
Technical state of equipm.	0.195**	0.067	0.177*	0.061	0.187	0.064	0.200*	0.069
	(0.04)		(0.08)		(0.14)		(0.08)	
Pred. Prob. R&D	0.714**	0.246	1.368**	0.474	1.920**	0.654	0.911*	0.315
	(0.20)		(0.36)		(0.56)		(0.45)	
Industry, Region, Year	Yes		Yes		Yes		Yes	
N	9,317		2,980		1,172		1,808	
Bootstrap reps.	100		100		100		100	
Log likelihood	-5643.51		-1812.194		-699.52		-1096.77	
Pseudo R2	0.111		0.122		0.111		0.099	

Note: Clustered s.e. at the firm level in parentheses. Reference groups: medium-sized firms, age class ≥20 years, *Significance at p < .05 level, **Significance at p < .01 level.

The first two columns include the entire sample of firms separated for the two sectors. As the positive and statistically significant coefficient of R&D engagement shows, the central tenet of the knowledge production model holds. Firms engaging in R&D exhibit a higher likelihood of being innovative in both manufacturing and knowledge-intensive services. As the next two columns show, this holds for larger firms, and also for micro firms in the KIS industries; even if the marginal effect for micro firms is half that of SMEs. Interestingly enough, among micro firms the skills variable seems to “compensate” for the lower marginal effect of R&D on the probability of innovation: highly skilled employees unfold nearly the same marginal effect on the probability of introducing at least one innovation as does R&D engagement. For SMEs, highly skilled employees are a much less powerful predictor of innovation.

The second striking result when comparing manufacturing with KIS-industries concerns again firm size. The coefficients of all firm-size class dummies are negative and statistically significant for manufacturing, suggesting that in this sector, even after controlling for R&D engagement, firm size tends to be positively related with the likelihood of innovating. When the likelihood of innovating is estimated for knowledge intensive service firms, the coefficients of the dummy variables for the different firm size classes are almost never statistically significant. For knowledge intensive service firms, it seems that firm size does not adversely influence the likelihood of innovative activities; again except for the very small firms with less than five employees.

There are similarities between the two sectors. The positive and statistically significant coefficients of skilled labor, technical state of equipment, and for training in both sectors are consistent with the knowledge production model in that they suggest that a higher amount of inputs generating knowledge results in a greater likelihood of innovative activity. This also holds for the KIS sector, even if these variables are not significant for the SME size class, probably because variation for firms with employees between 10 and 249 employees is low, nearly all KIS firms in the SME size class appear to be equipped with the newest state of apparatus and offer training (Table 1).

Finally, one important result with respect to young firms should be highlighted: the positive, and for KIS firms statistically significant, coefficient of the age class dummy variables for young firms implies that firm age and the likelihood of innovating are negatively related. Young firms are more likely to innovate successfully than mature firms in the KIS sector are. Looking more deeply into KIS-industries, we observe that the age class variable is only significant for micro firms. This would suggest that, after controlling for R&D engagement and other investments in knowledge such as skilled employees, training, technical equipment and investment, young firms enjoy an innovation advantage vis-à-vis their mature counterparts only among micro firms in these industries.

5.3. Third stage – productivity

The production function estimation is conducted using the ACF model as described in section 4.2. Given the data, we employ a sales production function with the log of revenue per employee used as the dependent variable. We do not impose the assumption of constant returns to scale, therefore keeping labor in the estimation. Note that cyclical effects on sales, sector differences, regional differences as well as differences due to age are accounted for in the first stage of the ACF procedure. The predicted probability of being an innovating firm from the second stage of the CDM model serves as innovation variable. The actual estimation is conducted by means of GMM (General Methods of Moments). Given the model outlined in section 4.2, the following set of instruments is employed: $Z = \{l_{it-1}, m_{it-1}, k_{it}, i^*_{it}\}$, with $E[\xi_{it}|Z] = 0$.[24]

The results of the production function estimations are presented in Table 4.[25] Columns 1 and 2 display the results for manufacturing and knowledge intensive service, columns 3 and 4 show the effects for micro and small firms in the KIS sector, respectively. As one would expect, labor has a much stronger effect in service firms than in

[24] Alternative specifications with additional instruments, such as k_{it-1} or i^*_{it-1} lead to roughly similar results. However, in such cases, the model is over-identified and, thus, the p-value of the Hansen-Test is not always larger than 0.1.

[25] For comparison, the results of the standard CDM, i.e. with OLS in the third stage, are shown in Table A.3. The respective coefficients for innovation are slightly higher with OLS. The same holds for the labor and the capital coefficients. In addition, the latter is always significant when estimating the production function with OLS.

manufacturing firms.[26] At the same time, investment in physical capital is insignificant for micro firms in the knowledge-intensive services.

Table 4: Production function estimates

	Manufacturing	Knowledge-intensive services		
	1-249	1-249	10-249	1-9
	α/s.e.	*α/s.e.*	*α/s.e.*	*α/s.e.*
Labor	-0.706**	-0.574**	-0.537**	-0.633**
	(0.03)	(0.08)	(0.08)	(0.13)
Capital	0.026**	0.032**	0.058**	0.028
	(0.00)	(0.01)	(0.02)	(0.02)
Material	0.687**	0.516**	0.497**	0.531**
	(0.02)	(0.06)	(0.06)	(0.07)
Pred. Prob. Innovator	0.408**	1.118**	0.749*	1.076**
	(0.08)	(0.22)	(0.34)	(0.25)
N	9,317	2,980	1,172	1,808
Bootstrap reps	100	100	100	100

Note: *Significance at p < .05 level, **Significance at p < .01 level.
Age, region, year and industry are controlled for in the first stage of ACF procedure.

With respect to innovation, our main variable of interest, we find in comparison to firms that do not innovate that innovating firms are causally able to increase their labor productivity. More specifically, if the probability to innovate increases by one percent, labor productivity increases by 1,1 percent for all firms in KIS (column 2). This result is in line with earlier research, for instance by Hall, et al. (2009) for Italian manufacturing firms.

5.4. Robustness Checks and Limitations

In our main estimation, we examine the effect of being an innovator instead of differentiating between product and process innovation. This procedure reflects the difficulty of clearly distinguishing between these two kinds of innovation among KIS

[26] Note that, because labor productivity is the dependent variable and constant returns to scale are not imposed, the coefficient for labor in Table 4 is actually $\alpha_1' = \alpha_1 - 1$. Thus, the lower the coefficient in the table, the higher the actual labor coefficient.

Table 5: Knowledge production function – process and product innovation

	Process Innovation								Product Innovation							
	Manufacturing		Knowledge-intensive services						Manufacturing		Knowledge-intensive services					
	1-249		1-249		10-249		1-9		1-249		1-249		10-249		1-9	
	α/s.e.	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx	*α/s.e.*	Mfx
1-4	-0.566**	-0.149	-0.551**	-0.129			0.049	0.009	-0.377**	-0.133	-0.387*	-0.135			0.000	0.000
employees	(0.12)		(0.20)				(0.13)		(0.11)		(0.18)				(0.11)	
5-9	-0.365**	-0.096	-0.505**	-0.118					-0.315**	-0.111	-0.368*	-0.128				
employees	(0.09)		(0.17)						(0.09)		(0.16)					
10-49	-0.147*	-0.039	-0.274	-0.064	-0.346*	-0.106			-0.137*	-0.048	-0.239	-0.084	-0.223	-0.078		
employees	(0.07)		(0.15)		(0.15)				(0.07)		(0.15)		(0.17)			
Age class	0.156**	0.041	0.209	0.049	0.130	0.040	0.197	0.036	0.062	0.022	0.291**	0.102	-0.000	-0.000	0.420**	0.144
(0-5 years)	(0.06)		(0.13)		(0.22)		(0.16)		(0.07)		(0.11)		(0.18)		(0.16)	
Age class	0.042	0.011	0.039	0.009	0.075	0.023	-0.032	-0.006	-0.011	-0.004	0.062	0.021	-0.004	-0.001	0.104	0.036
(6-19 years)	(0.04)		(0.09)		(0.14)		(0.15)		(0.04)		(0.08)		(0.13)		(0.11)	
Share high	0.286	0.075	0.337*	0.079	0.213	0.066	0.471*	0.086	1.623**	0.573	0.588**	0.205	0.294	0.102	0.828**	0.284
qual. empl.	(0.17)		(0.13)		(0.21)		(0.19)		(0.21)		(0.13)		(0.24)		(0.17)	
Training	0.275**	0.072	0.109	0.026	-0.212	-0.065	0.292**	0.053	0.310**	0.110	0.153*	0.053	0.058	0.020	0.189*	0.065
	(0.04)		(0.07)		(0.13)		(0.11)		(0.04)		(0.07)		(0.13)		(0.09)	
Techn. state	0.298**	0.078	0.259**	0.061	0.268	0.082	0.277**	0.051	0.170**	0.060	0.179*	0.062	0.179	0.063	0.196*	0.067
of equipm.	(0.04)		(0.10)		(0.14)		(0.10)		(0.04)		(0.08)		(0.13)		(0.08)	
Pred. Prob.	0.625**	0.164	1.186**	0.278	1.199*	0.368	1.295**	0.236	0.804**	0.284	1.298**	0.453	1.697**	0.592	1.005*	0.345
R&D	(0.19)		(0.38)		(0.52)		(0.50)		(0.21)		(0.35)		(0.54)		(0.47)	
Industry, Region, Year	Yes		Yes		Yes		Yes									
N	9,317		2,980		1,172		1,808									
Bootstrap reps.	100		100		100		100									
P-value for Wald test	0.000		0.000		0.000		0.000									
Rho	0.542		0.670		0.687		0.653									

Note: Clustered s.e. at the firm level in parentheses. Reference groups: medium-sized firms, age class ≥20 years, *Significance at $p < .05$ level, **Significance at $p < .01$ level.

firms. Nevertheless, in the robustness checks, we disentangle the effects of product and process innovation. In line with Hall, Lotti, and Mairesse (2009) and Baumann and Kritikos (2016) we estimate process and product innovation output in a bivariate probit model, taking into account the assumption that both are determined by the same firm characteristics. Table 5 presents the results for the second stage, the knowledge production function differentiated for product and process innovations. It shows that R&D engagement increases the probability of being innovative for both types of innovation. Similar to manufacturing, the marginal effects for product innovation are higher in the KIS industries than for process innovation. More importantly, it becomes clear that the age class dummy is only significant for product innovation: young firms are more likely to create a new product than are mature firms. One effect should be emphasized: The larger micro firms, with 5 to 9 employees, are able to transform innovation inputs into outputs with a similar likelihood (see column 3 in Table 3), but this does not hold when we estimate for product and process innovations separately. In other words, compared to their larger counterparts, micro firms are less likely to turn innovation inputs into new products.

By contrast, small firms (10-49 employees), are not adversely influenced by their size in comparison to medium sized firms when it comes to the likelihood of turning R&D investments into new products. Table 6 presents the results of the third stage of the innovation process, the production function, again estimated (as for Table 4) with the ACF approach. Disentangling the influence of product and process innovation on labor productivity confirms a well-established effect that is found in many empirical papers on manufacturing. While the positive influence of the predicted probability of a product innovation on labor productivity is highly significant, the effect of process innovation on labor productivity is insignificant.[27] As Table 6 reveals, this also holds for knowledge intensive services.

Table 6: Production function estimates

	Manufacturing	Knowledge-intensive services		
	1-249	1-249	10-249	1-9
	α/s.e.	*α/s.e.*	*α/s.e.*	*α/s.e.*
		-	-	-
Labor	-0.704***	0.562***	0.496***	0.650***
	(0.02)	(0.10)	(0.07)	(0.07)
Capital	0.026***	0.032***	0.055***	0.025
	(0.00)	(0.01)	(0.02)	(0.02)
Material	0.688***	0.511***	0.471***	0.551***
	(0.02)	(0.08)	(0.05)	(0.04)
Pred. Prob.	0.463***	0.937*	1.384**	1.404***
Product Innov.	(0.13)	(0.52)	(0.69)	(0.51)
Pred. Prob.	-0.098	0.134	-0.802	-0.602
Process Innov.	(0.19)	(0.77)	(0.80)	(0.95)
N	9,317	2,980	1,172	1,808
Bootstrap reps	100	100	100	100

Note: *Significance at p < .05 level, **Significance at p < .01 level.
Age, region, year and industry are controlled for in the first stage of ACF procedure.

Overall this robustness check confirms our main results and provides a clear answer to our main research question: KIS firms benefit from investments into R&D in the sense that their innovation outcomes causally increase their labor productivity.

Our analysis still faces a number of limitations that we will subsequently address. These limitations are mainly data driven. First, we are able to use only a dichotomous variable to measure R&D effort. As has been shown by Mairesse, Mohnen and Kremp (2005), such a dichotomous variable has less explanatory power than a continuous one. There is little that we can do about it, given our data. However, using qualitative information on R&D also has an advantage against censored quantitative information,

[27] See Hall (2011) for a more general discussion on why product more often than process innovation increases the labor productivity among firms.

namely, as Mairesse, Mohnen and Kremp (2005) clarify, that we do not have to account for the strict selectivity issue concerning R&D and innovation intensity for which Crepon, Duguet and Mairesse (1998) have to correct for in their specification.

Secondly, the measurement of innovation output remains rudimentary in two ways. Innovation output is still restricted to product and process innovation, although other types of non-technological innovations are receiving more attention, such as organizational innovation, marketing innovation, business model innovation, and social innovation. This becomes even more important as earlier research found contradicting evidence about the extent that non-technological innovation has an effect (Peters, Riley, et al. 2018) or "clearly has no" effect on productivity (Musolesi and Huiban 2010, 76). Future research, therefore, needs to better differentiate between technological and non-technological innovation outputs.

Another measurement issue concerns the fact that according to the CIS manual, innovation output is measured as a dichotomous variable. As larger firms tend to have more R&D activities than smaller ones, they should also be more likely to realize a higher number of innovative outcomes than smaller firms. Therefore, the knowledge production function estimates for the measures of firm size might be biased.

A last data limitation of this study concerns the lack of information on firm capital stock. This, however, is a common shortcoming in the literature (see *inter alia* Griffith, et al. 2006, Hall, Lotti and Mairesse 2009). Most research faces this issue and thus uses investment to proxy for the capital stock. We follow the literature by also making use of information on investment.[28]

[28] We follow Crass and Peters (2014) by replacing the log values of investment for non-investing firms with a constant (here: zero) and by adding a dummy variables for no-investment-observations. By doing so, the estimated output elasticity of investment is unaffected by the value of the constant and the estimation is not only restricted to investing firms.

6. Discussion and Conclusions

Most previous studies addressing the relationship between innovation and productivity either focus on the manufacturing sector or simply aggregate all industries across all observed sectors. Less is known about the role of innovative activities outside of manufacturing. Therefore, this paper analyzes the triad relationship between innovation input, principally R&D engagement, innovation output, and its impact on productivity in a non-manufacturing context – the knowledge intensive services (KIS). By using a database including both knowledge intensive service firms and manufacturing firms, this paper is able to explicitly probe whether services are different from manufacturing in terms of what influences firm innovation.

Using a broad and comprehensive database consisting of micro-, small-, and medium-sized firms in both sectors in Germany, the first important finding of this study is that, knowledge intensive services are able to generate innovative output by investing in R&D as is consistently found for manufacturing. To answer our second question, we incorporated the structural model of Ackerberg, Caves and Frazer (2015) into the third stage of the model of Crepon, Duguet and Mairesse (1998). We provide evidence that firms in KIS industries as well as in manufacturing firms are causally able to turn their innovation output into higher productivity.

Further results of this study suggest that the innovative activities of KIS firms do not simply mirror that of their manufacturing counterparts. First, a smaller share of knowledge intensive service firms formally invest in R&D than in manufacturing. At the same time, while a small firm size places a distinct burden on the innovation performance of manufacturing firms, the inherent size disadvantage confronting small firms is apparently less severe for knowledge intensive services. Even after controlling for R&D engagement in the likelihood of firm innovation, as well as for innovative activity in estimating firm productivity, the empirical results suggest that the role of firm size in innovation is for knowledge intensive services decidedly different from manufacturing firms. Both small and micro firms are willing to engage with similar probabilities in innovation activities (R&D) as are medium sized firms, with a relatively similar ability of transforming innovation inputs into innovation output. We also find that age effects are important, which are more relevant for the KIS sector than for manufacturing. In particular, young micro firms are better able to turn innovation inputs into new knowledge than are mature firms.

Other variables positively influence the probability of innovation output as well, with these variables exerting an influence irrespective of sector and firm size. Among other influences, innovation is sparked more frequently when the equipment is up to date as well as when firms have a higher share of employees who are trained and highly skilled, the latter being especially relevant for micro firms.

Overall, our findings have important policy implications. Policy needs to be cognizant that sweeping generalizations about promoting R&D, innovation, and productivity, across all types of firms and sectors may be less efficient. Rather, the relationships between R&D, innovation, and productivity are specific to the firm size and industry context. This suggests that policy efforts to stimulate innovation need to be sensitive to both aspects. Consider as one example the fact that the majority of micro- and small-firms in KIS industries - although successful innovators - do not formally budget for R&D. At the same time, Germany for instance is discussing the possibility of introducing tax credits for R&D investments, a benefit that exists already in a number of other countries. In this context, politicians emphasize that these benefits will be designed in a way to specifically help MSMEs in their innovation efforts, because these are said to refrain more strongly from R&D investments than larger firms. However, such tax benefits are futile, as the majority of these firms would not gain any tax advantages from benefits for R&D, because they do not formally employ R&D workers.

Future research should further analyze what kind of knowledge production is used and what kind of knowledge transfer is applied in those firms that do not invest in R&D activities, but successfully innovate. At the same time, research and policy need to ask what kind of instruments successfully incentivize MSMEs to become more innovative. For this, it is important to determine to what extent MSMEs currently refrain from formal innovation activities (see also Hottenrott and Peter 2012). Is it that they perceive these activities as too risky or is it that MSMEs would like to innovate but are not able to do so because they face financing constraints and lack external funding.

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Appendix

Table A.1: Descriptive statistics – manufacturing industry

	1-249	50-249	10-49	5-9	1-4
Sales (1,000 Euro)	8,408.40	22,265.50	3,217.67	507.33	199.32
Material (1,000 Euro)	5,135.94	13,840.10	1,796.67	263.95	102.06
Investment (1,000 Euro)	443.36	897.68	183.55	41.58	21.72
Labor	47.14	113.16	25.35	6.78	2.77
Share of R&D engagement	0.28	0.51	0.26	0.06	0.04
Share of innovators	0.58	0.76	0.59	0.39	0.32
Share of product innovators	0.55	0.73	0.56	0.38	0.31
Share of process innovators	0.21	0.33	0.20	0.11	0.07
Share of innovators without R&D	0.33	0.30	0.36	0.33	0.29
Age class (0-5 years)	0.07	0.06	0.08	0.09	0.09
Age class (6-19 years)	0.38	0.33	0.41	0.36	0.41
Age class (≥ 20 years)	0.55	0.61	0.52	0.55	0.50
Share of high skilled employees	0.06	0.09	0.07	0.03	0.02
Part of firm-group	0.14	0.29	0.10	0.03	0.02
Main sales market export	0.09	0.19	0.06	0.02	0.02
High competitive pressure	0.43	0.53	0.41	0.37	0.30
Limited	0.71	0.97	0.81	0.41	0.15
Profitable	0.42	0.43	0.44	0.41	0.35
Training	0.58	0.85	0.60	0.35	0.20
Technical state of equipment	0.58	0.65	0.60	0.49	0.45
Observations	9,317.00	2,946.00	3,662.00	1,376.00	1,333.00

Notes: The table displays means for continuous variables and shares otherwise.
(a) Based on observations in odd years.
Source: IAB Establishment Panel Survey 2009-2014. Own calculations.

Table A.2: Descriptive statistics – full dataset

	1-249	50-249	10-49	5-9	1-4
Sales (1,000 Euro)	6,832.84	21,534.18	3,008.96	498.53	200.91
Material (1,000 Euro)	4,070.21	13,167.72	1,599.20	233.02	92.41
Investment (1,000 Euro)	362.00	867.03	166.41	34.45	19.29
Labor	39.92	111.69	24.90	6.72	2.67
Share of R&D engagement	0.25	0.50	0.26	0.11	0.07
Share of innovators	0.55	0.76	0.59	0.41	0.34
Share of product innovators	0.53	0.73	0.56	0.40	0.33
Share of process innovators	0.20	0.34	0.21	0.12	0.08
Share of innovators without R&D	0.33	0.31	0.35	0.32	0.29
Age class (0-5 years)	0.09	0.06	0.08	0.10	0.12
Age class (6-19 years)	0.40	0.33	0.41	0.40	0.49
Age class (≥ 20 years)	0.51	0.60	0.51	0.50	0.40
Share of high skilled employees	0.10	0.11	0.11	0.11	0.06
Part of firm-group	0.13	0.29	0.12	0.04	0.02
Main sales market export	0.07	0.18	0.05	0.02	0.02
High competitive pressure	0.40	0.51	0.40	0.36	0.30
Limited	0.66	0.97	0.78	0.44	0.19
Profitable	0.45	0.44	0.47	0.45	0.40
Training	0.60	0.86	0.65	0.45	0.31
Technical state of equipment	0.63	0.67	0.65	0.58	0.57
Observations	12,297.00	3,190.00	4,590.00	2,052.00	2,465.00

Notes: The table displays means for continuous variables and shares otherwise.
(a) Based on observations in odd years.
Source: IAB Establishment Panel Survey 2009-2014. Own calculations.

Table A.3: Production function estimates with OLS, predicted innovation probability

	Manufacturing	Knowledge-intensive services		
	1-249	1-249	10-249	1-9
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Labor	-0.675***	-0.535***	-0.446***	-0.607***
	(0.01)	(0.03)	(0.04)	(0.04)
Capital	0.029***	0.044***	0.057***	0.044***
	(0.00)	(0.01)	(0.01)	(0.01)
Material	0.648***	0.480***	0.421***	0.515***
	(0.01)	(0.02)	(0.02)	(0.02)
Pred. Prob. Innov.	0.506***	1.105***	0.759***	1.054***
	(0.07)	(0.20)	(0.29)	(0.21)
Industry, region, year, age	yes	yes	yes	yes
Constant	3.781***	5.440***	6.061***	5.146***
	(0.08)	(0.17)	(0.23)	(0.27)
	9317	2980	1172	1808
Bootstrap reps.	100	100	100	100
Pseudo R2	0.853	0.685	0.697	0.656

Note: *Significance at p < .05 level, **Significance at p < .01 level.

Table A.4: Production function estimates with OLS, predicted probability process and product innovation

	Manufacturing	Knowledge-intensive services		
	1-249	1-249	10-249	1-9
	Coef./s.e.	Coef./s.e.	Coef./s.e.	Coef./s.e.
Labor	-0.669***	-0.533***	-0.435***	-0.601***
	(0.01)	(0.03)	(0.05)	(0.04)
Capital	0.029***	0.043***	0.054***	0.044***
	(0.00)	(0.01)	(0.01)	(0.01)
Material	0.647***	0.480***	0.415***	0.514***
	(0.01)	(0.02)	(0.02)	(0.02)
Pred. Prob. Product Innov.	0.588***	1.042***	1.300***	1.071**
	(0.12)	(0.35)	(0.46)	(0.46)
Pred. Prob. Process Innov.	-0.162	0.101	-0.688	0.002
	(0.18)	(0.46)	(0.53)	(0.83)
Industry, region, year, age	yes	yes	yes	yes
Constant	3.773***	5.472***	5.984***	5.161***
	(0.08)	(0.19)	(0.23)	(0.28)
N	9317	2980	1172	1808
Bootstrap reps.	100	100	100	100
Pseudo R2	0.853	0.685	0.701	0.656

Note: *Significance at p < .05 level, **Significance at p < .01 level.