R&D, EMBODIED TECHNOLOGICAL CHANGE, PRODUCERS-USERS INTERACTION, AND PRODUCTIVITY AT THE FIRM LEVEL: A GERMANY-ITALY COMPARISON*

by

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Abstract

This paper follows a knowledge production function approach to assess the contribution of R&D spending, the purchase of new machinery, and producers-users interaction to the productivity performance of German and Italian firms in manufacturing. For this purpose it employs micro-aggregated data from the First Community Innovation Survey. The regression analysis confirms the results of previous studies that technological change embodied in new machinery and capital equipment is a major factor affecting the productivity level of manufacturing firms in most industries (in particular in Italy), although the role of R&D activities is crucial for most firms in both countries, and that this is also the case in traditional consumer goods industries such as textiles, clothing, and leather & leather products. Conversely, only for Germany does producers-users interaction prove significantly to influence the productivity level of firms in certain industries.

Keywords: R&D; Innovation; Firm performance; Productivity; Germany; Italy
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1. Introduction

The first Community Innovation Survey (CIS) was launched in 1991 to store micro data on innovative activities from all member states of the European Union (EU) in one common, harmonised data base. As a direct, firm-based survey of innovation it is a useful source of information on innovative strategies, determinants of innovation, barriers to innovation, innovative efforts, and innovative results (Archibugi *et al*., 1994). In particular, it can be used to overcome the most frequent problems arising from the employment of traditional indirect measures of innovation, such as R&D, patents, and technological balance of payments. In effect, in spite of careful refinement and reclassification by statistical offices and scholars of technology, the traditional indicators are unable to handle all the problems raised by the implicit contrast between technological complexity and the economic value of innovations (R&D measures) and by the distinction between *inventions* and *innovations* (patent-based indicators). Conversely, by taking the firm as unit of analysis ("subject" approach) and exploring its innovative behaviour and activity, the CIS allows thorough investigation of the attitude of European firms towards innovation.

The aim of this paper is to assess the contribution of R&D spending, the purchase of new machinery, and the interaction with both suppliers and clients to the productivity performance of manufacturing firms in two of the largest EU member countries: Germany and Italy. Section 2 presents a simple production function model linking productivity to R&D, embodied technological change, and producers-users interaction. Section 3 describes the data set. Section 4 reports the results from estimation of the model introduced in Section 2. Finally, in Section 5 some concluding remarks are made.

2. Modelling framework: a knowledge production function perspective

According to Griliches (1979, 1984; cf. also Griliches and Mairesse, 1984), the crucial innovative input is new technological knowledge generated by R&D, and the relevant innovative output is technological knowledge resulting in patented innovations. The market value of the firm is therefore affected by an intangible "stock of knowledge" measured by past R&D and the number of patents. The current market value of the firm (V) may be therefore represented as

(1) $V = q(A + K)$

where A is current value of its conventional assets (plant, equipment, inventories, and financial assets), K denotes current value of its stock of knowledge, represented by past R&D and the number of patents, and *q* is the "current market valuation coefficient of the firm's assets, reflecting its differential risk and monopoly position" (Griliches, 1984, p. 249).

Besides the stock of knowledge, also the current innovative effort of the firm is likely to affect its market value and/or its productivity performance (cf. Klette, 1996). Taking Griliches' model as a point of departure, it is therefore possible to investigate the effect of both new technological knowledge generated by R&D, and technological knowledge embodied in the new machinery and capital equipment adopted by the firm on its productivity performance. Whereas R&D spending is a good proxy for the autonomous innovative capability of firms that produce the technology they use internally, expenditures on new machinery and capital equipment are a more reliable proxy for the overall technological level of firms that make little contribution to their own technology and are weak in terms of in-house R&D and engineering capabilities (cf. Pavitt, 1984; Santarelli and Sterlacchini, 1994).

Thus, we assume that a manufacturing firm has a "new input of knowledge" NK_{it} at time t resulting from research activities carried out within its R&D facilities, from the new machinery and capital equipment, as well as a series of sources including informal R&D, spillovers of formal research by other firms and universities, and technological knowledge originating from the interaction with both clients and suppliers of primary and intermediate goods. In fact, Andersen (1991) and Lundvall (1992) have shown that producers-users interaction significantly influences the overall innovative process, as typical non-standardised interfaces between groups of producers and groups of users of specific types of artefacts. This idea of interfirm relations can be traced back to Arrow (1973, p. 147) who (as quoted by Andersen, 1991, p. 135) asserted that "the customers of a firm are, to some extent, part of it … There are direct information flows from customers in the form of complaints, requests for alteration or special service … in addition to the anonymous alterations of demand at a given price which constitute the sole information link between a firm and its market in neoclassical theory". The resulting process of interactive learning therefore enables significant increases in productivity, irrespective of the fact that firms are involved in formal R&D activities and/or invest in new machinery with embodied technological change.

The effect of NK_{it} can be modelled in a total factor productivity (TFP) framework, using a Cobb-Douglas production function for the output of firm *i*:

(2) $Q_{it} = NK_{it}K_{it}L_{it}C_{it}M_{it}\exp(\varepsilon_{it})$

where Q_{it} is the output of firm *i* in year *t*¸ K_{it} is the stock of past knowledge, L_{it} stands for labour input, C_{it} denotes conventional capital inputs, M_i stands for material inputs, and $\exp(\varepsilon_{it})$ measures all the other factors that affect output. Accordingly, the level of total factor productivity (TFP_{it}) may be computed as

$$(3) TFP_{it} = \frac{Q_{it}}{NK_{it}K_{it}L_{it}C_{it}M_{it}}$$

Substituting (2) into (3) suggests that – assuming constant returns to scale at the firm level in the conventional inputs L_i, C_i, and M_i – the effect of both past and new knowledge can be estimated by regressing the log of Q_{it} on logs of NK_{it} and K_{it}. Thus, with

$$(4)\ NK_{it} = (MACH_{it} + R\&D_{it} + SUPPL_{it} + CLIENT_{it})$$

and

$$(5)\ K_{it} = (PAT_{Total} + R\&D_{Total})$$

where $MACH_{it}$ and $R\&D_{it}$ denote investment in new machinery with embodied technological change and current R&D expenditures respectively (new input of knowledge in the ith firm), and PAT_{Total} and $R\&D_{Total}$ stand for the stock of knowledge in the ith firm, the estimating model becomes

$$(6)\ Q_{it} = MACH_{it}R\&D_{it}SUPPL_{it}CLIENT_{it}PAT_{iTotal}R\&D_{iTotal}$$

At this point, the standard theoretical framework requires a complete history of R&D expenditures and patent activity for each firm (cf. Klette, 1996). However, since data limitations are particularly severe here, if one assumes that the stock of past knowledge ($PAT_{iTotal} + R\&D_{iTotal}$) is characterised by constant returns to scale at the firm level and is therefore proportional to firm size (EMPL), it may be represented as

$$(7)\ EMPL_{it} = (PAT_{iTotal} + R\&D_{iTotal})$$

Thus, substituting equation (7) in equation (6) yields

$$(8)\ Q_{it} = MACH_{it}R\&D_{it}SUPPL_{it}CLIENT_{it}EMPL_{it}$$

which links productivity to the firm’s commitment to direct and indirect innovative activities aimed at improving its productive efficiency. This is the form that we will use in the empirical analysis carried out in section 4.

3. Description of the data

In estimation of equation (8) we used a microaggregated version of the original CIS database for German and Italian manufacturing firms. The micro-aggregation procedure has been implemented at Eurostat using different techniques according to the type of variable. Thus, once quantitative, ordinal, and nominal variables had been identified, three micro-aggregation procedures were applied: individual ranking, individual ranking with “snake”, and classification by “similitude”. As regards quantitative variables, application of the individual ranking method required the primary variables to be ranked by ascending order, and individual observations to be grouped by three and then replaced with the cluster arithmetic mean. Ordinal variables were instead grouped into appropriate segments (“snakes”), and then ranked accordingly. In particular, once a segment of at least two ordinal variables had been identified, an arbitrary path (the snake) was chosen. The first three observations that the snake encountered were grouped together and then the original values were replaced with the median of the group. In the case of nominal variables, a simple method of grouping similar observations according to a particular segment was used: the most similar three observations were grouped together and the original values replaced by the cluster mode.

For the purposes of the present paper, mostly quantitative and ordinal variables are used, and they have therefore been developed by applying the same micro-aggregation procedure (the ranking). Although, in principle, application of different aggregation procedures does not necessarily lead to biased variables, it renders the econometric analysis carried out in Section 4 implicitly more reliable. In any case, as far as the total sales and the R&D expenditure variables are concerned, the quality of the resulting micro-aggregated data has been further checked by Eurostat on the basis of the following statistics: deciles, variance, marginal distribution, mean of the absolute difference between micro-aggregated and primary data, Pearson correlation coefficient. Moreover, a cleaning process was necessary to take logical relations between some of the variables into account.

However, to capture the impact of interaction with clients and suppliers of primary and intermediate goods on the firm’s productivity level, also ordinal variables have been employed. These are Likert scales with values ranging between 1 and 5 according to the ascending relative importance attributed by the firm to the interaction with clients and that with suppliers of primary and intermediate goods as external sources of information for innovation.

4. Empirical findings

4.1 - The empirical model

To test empirically the production function model presented in equation (8), we used the following specification

(9) $\ln S*E = \alpha_0 + \alpha_1 \ln R\&D*E + \alpha_2 \ln MACH*E + \alpha_3 \ln EMPL + \alpha_4 \ln RMIXPROD + \alpha_5 \ln SUPPL + \alpha_6 \ln CLIENT + \varepsilon$

with

S*E = total sales per employee

R&D*E = total R&D expenditures per employee

MACH*E = purchases of machinery (in value) per employee

EMPL = total employment in the firm

RMIXPROD = percentage of R&D related to product innovation

SUPPL = importance of suppliers of intermediate goods as a source of innovation (Likert scale)

CLIENT = importance of clients as a source of innovation (Likert scale)

The above specification rests on the assumption that the overall R&D activity is a cumulative, dynamic process characterised by large differences in innovative effort across firms within narrowly defined (NACE) industries (cf. Hall *et al.*, 1986). With respect to the theoretical model of equation (8), a new variable has been inserted (RMIXPROD) to capture the effect of the type of R&D on productivity. The underlying hypothesis is that the more a firm pursues an R&D activity devoted to new product development, the more its productivity level will rise. All the relevant data and information refer to 1992, and all ECUs amounts are in current 1992 ECUs. The summary statistics of the variables included in the analysis are reported in Tables A1 and A2 in the Appendix.

In order to carry out for Italy and Germany an OLS regression at the firm level for each manufacturing industry separately, we tested the absence of collinearity by computing the variance inflation factors (VIF) and the condition number of the regressor matrix, *k(**X**)* (cf. Appendix I and Tables A1 and A2 reported in Appendix II). As regards analysis of residuals, a consistent covariance matrix (White, 1980) was instead used in the case of heteroscedasticity (cf. Tables 1 and 2).

4.2 - Germany

When comparing the technological specialisation of a group of European countries, Guerrieri and Tylecote (1994), pointed out the presence in Germany of a general pattern of technological advantage in the mechanical and chemical technological families, while identifying a general weakness in electronics[1]. Although consistent with this and other views of an industrial system characterised by a homogeneous distribution of innovative capabilities among industries, the results obtained for Germany in the present paper (Table 1) highlight some peculiarities. Surprisingly, as regards the influence of the firms' direct commitment to innovative activities on productivity, the estimated coefficient of the R&D variable is negative, and significant at the 99 per cent confidence level in the case of four industries (food & beverages, wood & wooden products, pulp & paper, chemicals), whereas it carries the positive (and equally significant) sign for textiles, leather & leather products, printing & publishing, transformation of other minerals, office machinery & computers, TV & telecommunications equipment, and instruments.

The result for chemicals, along with the non significant (although positive) coefficient of the RMIXPROD variable, indirectly supports the assumption that the type of competition in the product market affects the incentives for carrying out R&D (Vickers, 1986). Thus, in a highly competitive market like that for chemicals in Germany, it is very likely that a firm's R&D intensity is positively correlated with its probability of discovering a new item but, at least initially, negatively correlated with its productivity level. In effect, not always and not necessarily does the development of entirely new chemical products result in more sales per employee, due to the fact that demand conditions usually do not adjust simultaneously to changes in supply conditions (Mowery and Rosenberg, 1979).

Different is instead the case of firms in high-tech industries such as office machinery & computers, TV & telecommunications equipment, and instruments. As already shown by Harhoff (1999), they extract significant productivity gains from their own R&D activities, with an R&D elasticity of sales around 12 percent.

The positive sign of the R&D variable for firms belonging to two (textiles, leather & leather products) out of three industries composing the "fashion" sector (the third being clothing) is presumably consequent on the dramatic process of technological change that occurred in the fashion sector during the 1980s (cf. Humbert, 1988), which fostered the acquisition by most

[1] In particular, through computation of the Balassa index of Revealed Technological Competitive Advantage.

firms of an autonomous innovative capability[2]. Thus, firms usually perceived as supplier dominated ones in Pavitt's (1984) sense, not only display a particularly high elasticity of productivity to embodied technological change, but they also obtain from R&D activities the technological inputs needed to improve their productivity levels.

In five industries (clothing, wood & wooden products, printing & publishing, mechanical engineering, electrical engineering) the fact that firms carry out an higher percentage of R&D related to product innovation results in a lower productivity level, i.e. the estimated coefficient is negative and statistically significant at the 99 per cent level. Evidently, also in the case of such industries the search for new products results in increased productivity levels only in the long run.

With respect to embodied technological change as well**,** there are certain industries in which, at the firm level, a higher level of expenditures in new machinery per employee is associated with lower productivity[3]; these are: printing & publishing, office machinery & computers, instruments. Conversely, in food & beverages, textiles, wood & wooden products, chemicals, and TV & telecommunications equipment the coefficient displays positive sign and is highly significant. A possible explanation for these controversial results may be the uneven utilisation of computer integrated manufacturing (CIM) components in the late 1980s in Germany. As aptly shown by Kohler and Schmierl (1991), computers were particularly widespread in the administrative area (financial and pay-roll accounting), whereas other electronic devices, such as robots, computer based assembly systems, and material flow systems still had low diffusion rates (below 10% of potential adopters). As a consequence, it may be that a large proportion of those firms that invested more heavily in new machinery in 1992 replaced individual CNC machines with computer integrated and flexible manufacturing systems. Since we are using as dependent variable total sales per employee in 1992, it is very likely that for the majority of firms in certain industries the adoption of machinery embodying radical technological change negatively affected productivity in the first year, due to high adjustment costs (cf. also Altmann *et al*. (1992).

In the case of office machinery & computers also the EMPL variable has a negative (and significant at the 99% confidence level) sign, and also in the cases of textiles, wood & wooden products, transformation of other minerals, and electrical engineering. The same variable instead displays a positive and highly significant sign for food & beverages, leather & leather products, pulp & paper, printing & publishing, petroleum refining, chemicals, metal working, TV & telecommunications equipment, instruments, and motor vehicles. Whereas office machinery & computers, and transformation of other minerals are industries dominated by

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[2] As regards textiles, it is worth pointing out that also in 1992 Germany was the biggest textile exporter (accounting for 12% of world trade) with Italy (8.7%) coming third (cf. Gruber, 1998).

[3] With the estimated coefficient displaying the negative sign and significant at the 99% confidence level.

large firms (cf. Davies and Sembenelli, 1993), in textiles, wood & wooden products, food & beverages, leather & leather products, metal working, and instruments, SMEs hold a relatively larger market share. Thus, in the first two industries large firms (with a larger stock of past R&D and patents) are probably less efficient, whereas in textiles, and wood & wooden products analogous considerations apply to SMEs. In the remaining industries, technology is instead characterised by increasing returns to scale and, other things being equal, corresponding to a larger employment size is a higher level of productivity.

- table 1 about here -

Producers-users interaction proves to play a crucial function in industries characterised by a large presence of SMEs (including textiles, clothing, leather & leather products, instruments), irrespective of whether they are supplier dominated or science based in Pavitt's (1984) sense. In fact, as shown by Harhoff (1997), R&D expenditures and investment are to a considerable extent sensitive to cash flow in the case of German small firms. Thus, a close interaction with producers and users serves to overcome their technological fragility consequent upon financing constraints. Conversely, an increase in the perceived importance of the interaction with clients negatively affects productivity in the following industries: wood & wooden products, chemicals, transformation of other minerals, office machinery & computers, electrical engineering, TV & telecommunications equipment, and motor vehicles. This finding suggests that, although firms in such industries are able to transform the clients' requirements in sources of innovation, they obtain a negative impact, in terms of total sales per employee, once they modify their organisational structure to cope with these requirements. More puzzling is interpretation of the negative sign, significant at the 99 per cent confidence level, displayed by the coefficient of the SUPPL variable. Also in this case, however, one may intuitively argue that technological advancements induced by the interaction with suppliers of primary and intermediate goods does not immediately and necessarily result in increases in productivity, but rather in costly re-organisation of productive activity.

4.3 - Italy

As regards Italy, Guerrieri and Tylecote (1994) have shown that the specialisation pattern of the manufacturing industries is more heterogeneous than in Germany. In particular, electronics and chemicals achieve bad technological performance, whereas Italy is particularly strong technologically in the mechanical family and in traditional consumer goods industries[4].

[4] These results are consistent with the approach that emphasises the general correspondence between competitive advantage and technological performance (cf. Amendola *et al*., 1993; Pantiglioni and Santarelli, 1998)

The above picture is to a large extent confirmed by the results of sectoral regressions reported in table 2, which emphasise the impact of the overall innovative activities carried out directly and autonomously by firms in most industries on productivity. The estimated coefficient of the R&D variable is positive and significant at the 99 per cent confidence level for firms in ten out of twenty-one industries – including textiles, clothing, leather & leather products, chemicals, mechanical engineering, office machinery & computers, and motor vehicles. This result is of particular importance in relation to the three industries composing the "fashion" sector (textiles, clothing, leather & leather products), which account for 24 per cent of total employment, 16.5 per cent of value added, and 17 per cent of exports in Italian manufacturing[5]. Estimation of an augmented production function model therefore yields a picture to some extent in contrast with the usual view of Italian manufacturing as characterised by a segmented, dualistic structure where a few high-tech industries co-exist with a pool of traditional ones rather weak in terms of innovative capabilities (cf., among others, Leoncini *et al*., 1996). In fact, as aptly shown by Sterlacchini (1998), since the early 1990s, in Italy, even firms belonging to traditional consumer goods industries have started to undertake autonomous innovative activities and to introduce R&D labs. Accordingly, they are probably losing the characteristic that typified them until the mid-1980s, namely their extraction from embodied technological change of most of the technological knowledge that they used, carrying out informal rather than formal R&D activities (cf. Santarelli and Sterlacchini, 1990; Malerba, 1993).

A higher percentage of R&D devoted to product innovation (RMIXPROD) has a positive and significant impact on productivity in the case of firms in leather & leather products, rubber & plastics, mechanical engineering, and instruments, whereas past knowledge (EMPL) proves to be significant at the 99 per cent confidence level for clothing, wood & wooden products, petroleum refining, transformation of other minerals, fabricated metal products, and office machinery & computers.

- table 2 about here -

These results are even more significant if we use Pavitt's (1984) taxonomy as an analytical device: those firms that, by definition, belong to the category of supplier dominated firms (i.e. those in traditional consumer goods industries) find both present and past innovative capability to be an important productivity-stimulating factor. Turning to embodied technological change (MACH), this variable obtains a positive and significant (at the 99 per cent confidence level) coefficient in the firm level regressions carried out for seven industries: textiles, clothing, leather & leather products, transformation of other minerals, fabricated metal products,

[5] As shown by Colombo and Mosconi (1995), the diffusion of Flexible Automation production and design/engineering technologies in Italian manufacturing (in particular among firms in metalworking) has been fostered by learning-by-using effects connected with experience in previously available technologies.

mechanical engineering, electrical engineering. As regards the EMPL variable, its coefficient is positive and significant at the 99 per cent confidence level for six industries (including clothing, wood & wooden products, and office machinery & computers), and positive and significant at the 90 or 95 per cent confidence level in four other industries (including leather & leather products). Larger firms – which according to the theoretical assumptions presented in section 2 have a larger amount of past R&D and patents – are therefore characterised by higher productivity both in traditional consumer goods industries (clothing, wood & wooden products, and leather & leather products) and high-tech industries (office machinery & computers). But they also matter in scale intensive industries such as petroleum refining, and the transformation of other minerals besides fabricated metal products. Thus, a significant convergence emerges with Germany; namely that as far as the innovative activity/productivity relationship is concerned, in both countries larger firms have in some cases a competitive advantage with respect to smaller ones. Conversely, in the remaining industries larger firms do not have a competitive advantage with respect to smaller ones – a result consistent with those of previous studies emphasising the virtuous role of small firms belonging to industries like chemicals and electrical engineering (cf. Audretsch *et al*., 1998) and/or localised within industrial districts in the Italian economy (cf. among others, Brusco, 1986).

The case of producers-users interaction is different, however: only in the case of firms belonging to the printing & publishing industry is the estimated coefficient of the SUPPL variable significant, although only at the 95 per cent confidence level, whereas that of the CLIENT variable is never statistically significant. This entails that in 1992 most Italian firms still paid scant if any attention to those marketing activities which allow adaptation of the product to market requirements, with the sole exception of those involved in sub-contracting activities.

5. Concluding remarks

In comparing German and Italian manufacturing, we find significant evidence that technological change embodied in new machinery and capital equipment is a major factor affecting the productivity level of firms in most Italian industries, in particular those belonging to the "fashion" and the mechanical filieres in which the country holds traditionally a competitive advantage. Nonetheless, the role of R&D activities is crucial for most firms in both countries, and not only in high-tech industries (such as office machinery & computers) but also in traditional consumer goods ones. Conversely, only for Germany does producers-users interaction significantly influence the productivity level of firms in certain industries.

Thus, technology in a broad sense turns out to be a factor substantially affecting the productivity performance of manufacturing firms in both Italy and Germany, although the two countries still display a significant difference in the way that the various potential sources of new technology are beneficial to the firms.

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Table 1 – Production function estimates for all (pseudo-)firms by industry (Germany)

Industries by NACE co.	R&D*E	MACH*E	EMPL	RMIXPROD	CLIEN	SUPPL	Constant	R^2 adj.	F-stat	White[a]
15 - Food & beverages	-0.11*** (0.01)	0.16*** (0.02)	0.25*** (0.01)	0.77*** (0.05)	-0.16** (0.07)	-0.1** (0.05)	4.67*** (0.11)	0.99	995.32***	13.33
17 - Textiles	0.18*** (0.03)	0.06*** (0.02)	-0.27*** (0.03)	0.51*** (0.03)	1.61*** (0.11)	0.86*** (0.08)	3.25*** (0.20)	0.60	285***	8.90
18 - Clothing	0.08** (0.03)	-0.04 (0.04)	-0.06* (0.04)	-1.03*** (0.15)	2.26*** (0.18)	0.65*** (0.13)	0.35 (0.38)	0.37	36.52***	14.95
19 - Leather & leat. prod.	0.84*** (0.09)	0.08 (0.10)	0.70*** (0.05)	0.53 (0.37)	2.74*** (0.26)	0.23*** (0.08)	-1.43** (0.58)	0.78	219.92***	13.00
20 - Wood & wood. pr.	-1.49*** (0.04)	0.23*** (0.01)	-0.53*** (0.01)	-0.37*** (0.05)	-1.75*** (0.04)	0.89*** (0.02)	6.65*** (0.10)	0.80	737.00***	12.25
21 - Pulp & paper	-0.08*** (0.02)	0.07*** (0.02)	0.34*** (0.03)	0.23*** (0.05)	1.17*** (0.15)	-0.65*** (0.12)	2.63*** (0.26)	0.50	56.34***	11.10
22 - Printing & publish.	0.04*** (0.00)	-0.66*** (0.01)	0.03*** (0.00)	-1.01*** (0.01)	1.39*** (0.01)	0.32*** (0.00)	0.44*** (0.03)	0.99	10078.84***	11.09
23 - Petroleum refining	-0.01 (0.13)	-0.12* (0.06)	0.16*** (0.04)	-0.67* (0.34)	-0.27 (0.20)	-0.61*** (0.12)	4.98*** (0.35)	0.37	5.52***	11.44
24 - Chemicals	-0.11*** (0.06)	0.20*** (0.07)	0.33*** (0.10)	0.22 (0.24)	-1.61*** (0.42)	-0.11 (0.14)	6.39*** (0.63)	0.98	1391.73***	20.06*
25 - Rubber & plastics	0.23** (0.01)	0.00 (0.06)	-0.05 (0.14)	0.11 (0.15)	-0.01** (0.45)	0.21 (0.21)	5.90*** (0.06)	0.97	563.80***	24.73**
26 - Transf. of other min.	0.09*** (0.02)	0.03** (0.01)	-0.05*** (0.01)	0.36*** (0.03)	-0.84*** (0.10)	-0.14*** (0.03)	6.22*** (0.17)	0.22	50.82***	17.18
27 - Metal working	0.00 (0.02)	0.02 (0.02)	0.04*** (0.01)	0.13*** (0.02)	0.10 (0.08)	0.01 (0.06)	4.38*** (0.15)	0.10	12.06***	14.80
28 - Fabric. metal prod.	0.14 (0.12)	0.13 (0.12)	0.16 (0.12)	0.63*** (0.21)	0.50 (0.68)	-0.10 (0.46)	3.78*** (1.34)	0.98	1419.75***	30.79***
29 - Mechan. engineering	-0.09 (0.09)	0.07 (0.07)	-0.01 (0.07)	-0.45*** (0.12)	-0.07 (0.44)	-0.15 (0.14)	5.02*** (0.76)	0.98	4582.43***	60.85***
30 - Office mach.& comp.	0.20*** (0.02)	-0.48*** (0.02)	-0.09*** (0.01)	-0.13 (0.08)	-0.44*** (0.13)	-0.06 (0.07)	4.49*** (0.18)	0.40	96.73***	15.12
31 - Electrical. engin.	0.09 (0.06)	0.12 (0.16)	-0.12** (0.06)	-0.34*** (0.03)	-0.45*** (0.13)	-1.09*** (0.05)	7.11*** (0.24)	0.99	4220.99***	23.07**
32 - TV & telecom. eq.	0.11*** (0.02)	0.24*** (0.02)	0.07*** (0.01)	0.25*** (0.07)	-3.45*** (0.20)	0.52*** (0.08)	9.10*** (0.35)	0.58	161.91***	16.71
33 - Instruments	0.08*** (0.01)	-0.08*** (0.01)	0.05*** (0.00)	0.07*** (0.01)	0.26*** (0.04)	-0.08*** (0.02)	3.59*** (0.08)	0.16	104.47***	13.49
34 - Motor vehicles	0.01 (0.01)	-0.02** (0.01)	0.10*** (0.01)	-0.04* (0.02)	-0.39*** (0.06)	0.21*** (0.04)	4.18*** (0.11)	0.27	50.55***	18.41
35 - Oth. means of transp.	-0.11 (0.10)	0.10 (0.08)	0.12 (0.08)	-0.91** (0.36)	1.79*** (0.58)	0.19 (0.34)	1.24 (1.56)	0.99	10183.57***	20.92*

* = significant at the 90% level of confidence; ** = significant at the 95% level of confidence; *** = significant at the 99% level of confidence.
[1] Null hypothesis: homoskedasticity; in the case of heteroskedasticity (at least 90% significance level) a consistent covariance matrix has been used (White's correction).
Standard error in brackets

Table 2 – Production function estimates for all (pseudo-)firms by industry (Italy)

Industries by NACE co.	R&D*E	MACH*E	EMPL	RMIXPROD	CLIEN	SUPPL	Constant	R^2 adj.	F-stat	White[a]
15 - Food & beverages	0.14*** (0.05)	0.18** (0.08)	0.05 (0.07)	-0.03 (0.12)	0.04 (0.11)	-0.07 (0.14)	4.98*** (0.31)	0.23	10.26***	9.49***
17 - Textiles	0.17*** (0.03)	0.11*** (0.03)	0.06 (0.04)	0.14** (0.07)	0.05 (0.08)	0.00 (0.08)	4.27*** (0.21)	0.29	14.69***	14.70
18 - Clothing	0.33*** (0.05)	0.16*** (0.06)	0.24*** (0.07)	0.11 (0.09)	0.03 (0.13)	-0.16 (0.18)	3.56*** (0.39)	0.44	8.88***	10.80
19 - Leather & leat. prod.	0.10*** (0.03)	0.1*** (0.03)	0.11** (0.05)	0.24*** (0.08)	-0.18 (0.08)	-0.07 (0.09)	4.63*** (0.24)	0.36	12.73***	17.22
20 - Wood & wood. pr.	0.07 (0.04)	0.07 (0.05)	0.19*** (0.07)	-0.06 (0.11)	-0.01 (0.09)	-0.16 (0.12)	4.14*** (0.41)	0.26	4.64***	12.81
21 - Pulp & paper	-0.01 (0.06)	0.05 (0.05)	0.03 (0.09)	0.16 (0.13)	0.08 (0.12)	0.07 (0.15)	4.85*** (0.43)	0.26	5.73***	23.78**
22 - Printing & publish.	0.10 (0.06)	-0.13 (0.08)	-0.11 (0.11)	0.20* (0.11)	-0.31 (0.19)	0.53** (0.26)	5.22*** (0.65)	0.28	4.11***	13.64
23 - Petroleum refining	0.07 (0.17)	0.17 (0.17)	0.62*** (0.13)	0.49 (0.79)	-0.15 (0.41)	-0.50 (0.52)	3.98*** (0.86)	0.40	3.12**	14.08
24 - Chemicals	0.09*** (0.03)	0.01 (0.02)	0.01 (0.02)	0.13* (0.07)	0.02 (0.08)	0.10 (0.08)	5.02*** (0.14)	0.32	24.72***	22.33**
25 - Rubber & plastics	0.05* (0.02)	0.04 (0.03)	0.00 (0.03)	0.14*** (0.05)	-0.04 (0.06)	0.06 (0.07)	4.94*** (0.19)	0.46	28.82***	10.66
26 - Transf. of other min.	0.02 (0.03)	0.08*** (0.02)	0.08*** (0.03)	-0.02 (0.05)	-0.06 (0.05)	-0.13 (0.07)	4.52*** (0.16)	0.31	16.81***	16.90
27 - Metal working	0.12** (0.05)	0.12** (0.05)	0.10* (0.06)	0.03 (0.13)	0.08 (0.16)	-0.13 (0.14)	4.33*** (0.48)	0.16	3.73***	20.05*
28 - Fabric. metal prod.	0.10*** (0.04)	0.07*** (0.02)	0.10*** (0.02)	0.06 (0.05)	0.02 (0.08)	-0.04 (0.06)	4.17*** (0.17)	0.10	7.91***	58.55***
29 - Mechan. engineering	0.09*** (0.02)	0.07*** (0.02)	0.06** (0.03)	0.08*** (0.03)	0.02 (0.04)	-0.04 (0.03)	4.5*** (0.13)	0.09	18.30***	149.07***
30 - Office mach.& comp.	0.24*** (0.07)	-0.05 (0.08)	0.18*** (0.05)	-0.35** (0.17)	-0.52 (0.33)	0.04 (0.19)	4.23*** (0.54)	0.82	22.82***	8.80
31 - Electrical. engin.	0.03 (0.03)	0.15*** (0.04)	0.03 (0.03)	0.10* (0.06)	-0.05 (0.07)	-0.04 (0.07)	4.64*** (0.17)	0.41	31.31***	68.60***
32 - TV & telecom. eq.	0.17*** (0.05)	0.02 (0.05)	0.04 (0.04)	0.11 (0.13)	-0.07 (0.12)	0.07 (0.15)	4.27*** (0.26)	0.80	77.50***	14.25
33 - Instruments	0.06** (0.02)	-0.03 (0.03)	0.06** (0.03)	0.17*** (0.06)	-0.01 (0.08)	0.05 (0.07)	4.4*** (0.17)	0.60	45.05***	7.64
34 - Motor vehicles	0.1*** (0.04)	0.05* (0.03)	0.04 (0.03)	-0.04 (0.06)	0.05 (0.08)	0.05 (0.10)	4.28*** (0.17)	0.64	40.49***	7.71
35 - Oth. means of transp.	0.09* (0.05)	-0.03 (0.05)	-0.07* (0.04)	0.24* (0.14)	-0.14 (0.14)	-0.12 (0.14)	5.26*** (0.28)	0.25	4.73***	11.46

* = significant at the 90% level of confidence; ** = significant at the 95% level of confidence; *** = significant at the 99% level of confidence.

[1] Null hypothesis: homoskedasticity; in the case of heteroskedasticity (at least 90% significance level) a consistent covariance matrix has been used (White's correction).

Standard error in brackets.

APPENDIX I

Multicollinearity proved to be largely absent in our data. However, when carrying out OLS estimation for Germany, in the case of leather & leather products, and wood & wooden products, computation of both VIF and *k(**X**)* signalled the presence of a high degree of multicollinearity. Following Sengupta and Bhimasankaram (1997), we therefore decided to augment the ***X*** matrix by adding a new set of information represented by the cases excluded from the regression analysis for missing values, and then replacing them with the arithmetic mean. To obtain a reliable measure of the influence of the additional observation set, named ***I***, on collinearity, we considered the ratio

$$\delta_I = \frac{k_{(X)} - k_{(X+I)}}{k_{(X+I)}}$$

where $k_{(X)}$ is the condition number of ***X*** and $k_{(X+I)}$ the condition number of the matrix obtained by adding the new set of information ***I*** (cf. Hadi and Wells, 1990). A negative value of d_I indicates a collinearity enhancing set, while a positive one indicates a collinearity reducing set. For both industries, we in fact obtained positive values of d_I (respectively 0.44 and 1.05).

Moreover, introduction of the new cases in the analysis allowed us, firstly, to keep the maximum of sampling information, and, secondly, by replacing missing values with the arithmetic mean, to add those cases that minimise the variance of the OLS estimator (Silvey, 1969). Finally, we carried out the regression analysis on the composed matrix ***(X+I)***, obtaining a significant reduction in the degree of collinearity.

APPENDIX II

Table A1 – Descriptive Statistics (Germany)

NACE	Variable	Mean	St. Dev.	VIF	NACE	Variable	Mean	St. Dev.	VIF
15)	S*E	4.74	0.69		**26)**	S*E	4.43	0.53	
N. of cases=1145	R&D*E	0.65	1.25	1.58	N. of cases=1085	R&D*E	0.56	1.12	1.90
	MACH*E	-1.83	1.15	1.68		MACH*E	-2.14	1.35	1.56
	EMPL	4.58	1.52	1.26		EMPL	4.40	1.52	1.69
	RMIXPROD	-0.48	0.32	1.19		RMIXPROD	-0.49	0.47	1.04
	CLIENT	1.38	0.31	1.99		CLIENT	1.49	0.18	1.42
k(X)=22.66	SUPPL	1.20	0.32	1.36	k(X)=35.51	SUPPL	1.01	0.45	1.09
17)	S*E	4.82	1.12		**27)**	S*E	4.49	0.41	
N. of cases=1124	R&D*E	0.58	1.18	2.27	N. of cases=580	R&D*E	0.34	1.04	1.09
	MACH*E	-2.26	1.18	1.60		MACH*E	-1.92	1.10	1.56
	EMPL	4.01	1.23	2.14		EMPL	4.76	1.45	1.59
	RMIXPROD	-0.92	0.68	1.19		RMIXPROD	-1.47	0.83	1.45
	CLIENT	1.39	0.22	1.20		CLIENT	1.48	0.24	1.43
k(X)=26.65	SUPPL	1.08	0.27	1.13	k(X)=25.81	SUPPL	1.16	0.40	1.97
18)	S*E	4.78	0.61		**28)**	S*E	4.36	0.74	
N. of cases=368	R&D*E	0.80	1.29	1.93	N. of cases=3953	R&D*E	0.26	1.34	1.97
	MACH*E	-2.81	1.18	3.90		MACH*E	-2.24	1.21	1.73
	EMPL	5.19	1.09	2.40		EMPL	3.94	1.17	1.16
	RMIXPROD	-0.38	0.32	3.36		RMIXPROD	-0.62	0.69	1.39
	CLIENT	1.56	0.15	1.07		CLIENT	1.48	0.20	1.22
k(X)=43.16	SUPPL	1.02	0.33	3.13	k(X)=30.87	SUPPL	1.10	0.34	1.36
19)	S*E	4.50	1.32		**29)**	S*E	4.52	0.57	
N. of cases=384	R&D*E	-0.67	0.99	7.80	N. of cases=6054	R&D*E	0.85	1.18	1.22
	MACH*E	-2.25	0.65	4.48		MACH*E	-2.08	1.19	1.35
	EMPL	4.33	1.32	4.05		EMPL	4.30	1.46	1.47
	RMIXPROD	-0.36	0.24	7.73		RMIXPROD	-0.30	0.50	1.09
	CLIENT	1.33	0.37	9.29		CLIENT	1.50	0.17	1.03
k(X)=50.29	SUPPL	0.70	0.64	2.70	k(X)=31.57	SUPPL	1.11	0.38	1.03
20)	S*E	4.49	0.69		**30)**	S*E	4.62	0.63	
N. of cases=1117	R&D*E	-0.90	0.32	2.32	N. of cases=849	R&D*E	1.13	1.58	3.71
	MACH*E	-1.50	1.08	1.68		MACH*E	-1.85	0.99	1.61
	EMPL	3.71	0.78	1.64		EMPL	3.48	1.67	1.92
	RMIXPROD	-1.23	0.24	1.57		RMIXPROD	-0.29	0.23	1.17
	CLIENT	1.39	0.32	2.10		CLIENT	1.48	0.15	1.29
k(X)=31.44	SUPPL	0.91	0.59	1.44	k(X)=35.68	SUPPL	1.03	0.44	3.47
21)	S*E	4.85	0.56		**31)**	S*E	4.93	0.90	
N. of cases=335	R&D*E	0.14	1.32	1.25	N. of cases=1290	R&D*E	1.31	1.12	1.32
	MACH*E	-1.79	1.48	1.58		MACH*E	-1.91	0.84	1.48
	EMPL	4.90	1.21	2.94		EMPL	3.87	1.83	1.27
	RMIXPROD	-0.83	0.77	3.23		RMIXPROD	-0.46	0.73	1.58
	CLIENT	1.51	0.17	1.30		CLIENT	1.33	0.34	2.09
k(X)=34.35	SUPPL	1.30	0.23	1.50	k(X)=23.35	SUPPL	1.01	0.56	1.46
22)	S*E	4.71	0.23		**32)**	S*E	4.27	0.64	
N. of cases=805	R&D*E	0.91	0.53	2.01	N. of cases=699	R&D*E	1.91	1.02	1.72
	MACH*E	-2.06	0.22	1.44		MACH*E	-2.33	0.90	1.81
	EMPL	5.42	0.51	1.38		EMPL	3.96	1.41	1.30
	RMIXPROD	-0.64	0.20	2.26		RMIXPROD	-0.14	0.28	1.70
	CLIENT	1.20	0.19	7.08		CLIENT	1.55	0.10	1.59
k(X)=101.99	SUPPL	1.22	0.44	5.33	k(X)=69.83	SUPPL	1.21	0.23	1.57
23)	S*E	5.28	0.40		**33)**	S*E	4.32	0.40	
N. of cases=48	R&D*E	1.13	0.99	7.95	N. of cases=3231	R&D*E	1.30	1.18	1.11
	MACH*E	-2.17	1.07	1.98		MACH*E	-2.10	0.92	1.08
	EMPL	4.51	1.37	1.56		EMPL	4.20	1.47	1.11
	RMIXPROD	-0.25	0.40	8.64		RMIXPROD	-0.57	0.74	1.17
	CLIENT	1.43	0.30	1.57		CLIENT	1.50	0.15	1.08
k(X)=20.53	SUPPL	0.73	0.60	2.19	k(X)=37.02	SUPPL	1.14	0.34	1.06
24)	S*E	4.73	0.68		**34)**	S*E	4.37	0.36	
N. of cases=1670	R&D*E	1.10	1.31	1.10	N. of cases=821	R&D*E	0.44	1.36	1.04
	MACH*E	-1.70	1.23	1.18		MACH*E	-2.24	1.19	1.02
	EMPL	4.42	1.59	1.25		EMPL	4.90	1.58	1.05
	RMIXPROD	-0.38	0.39	1.07		RMIXPROD	-0.34	0.47	1.04
	CLIENT	1.43	0.19	1.14		CLIENT	1.51	0.18	1.04
k(X)=26.48	SUPPL	0.97	0.43	1.09	k(X)=30.06	SUPPL	1.15	0.28	1.03
25)	S*E	4.46	0.55		**35)**	S*E	4.48	0.38	
N. of cases=1641	R&D*E	0.28	1.41	1.99	N. of cases=393	R&D*E	0.35	1.26	1.83
	MACH*E	-1.76	1.64	1.89		MACH*E	-2.56	1.24	1.79
	EMPL	4.14	1.48	1.99		EMPL	4.50	1.29	2.11
	RMIXPROD	-0.71	0.73	1.16		RMIXPROD	-0.37	0.30	2.79
	CLIENT	1.42	0.24	1.71		CLIENT	1.38	0.13	1.51
k(X)=23.14	SUPPL	1.12	0.42	1.16	k(X)=49.79	SUPPL	1.35	0.17	1.17

Table A2 – Descriptive Statistics (Italy)

NACE	Variable	Mean	St. Dev.	VIF	NACE	Variable	Mean	St. Dev.	VIF

15)	S*E	5.48	0.94		**26)**	S*E	4.82	0.51	
N. of cases=281	R&D*E	0.27	1.33	1.17	N. of cases=300	R&D*E	0.40	1.09	1.11
	MACH*E	1.48	1.42	1.32		MACH*E	1.38	1.26	1.12
	EMPL	4.58	1.26	1.26		EMPL	4.40	1.07	1.09
	RMIXPROD	-0.65	0.57	1.03		RMIXPROD	-0.60	0.65	1.03
	CLIENT	0.99	0.55	1.22		CLIENT	0.92	0.56	1.02
k(X)=14.86	SUPPL	1.03	0.42	1.25	k(X)=14.94	SUPPL	0.97	0.41	1.03
17)	S*E	4.71	0.66		**27)**	S*E	4.96	0.70	
N. of cases=329	R&D*E	0.32	1.03	1.08	N. of cases=126	R&D*E	0.31	1.36	1.30
	MACH*E	1.22	1.19	1.22		MACH*E	1.52	1.34	1.13
	EMPL	4.38	0.96	1.22		EMPL	5.02	1.35	1.21
	RMIXPROD	-0.48	0.50	1.08		RMIXPROD	-0.91	0.75	1.06
	CLIENT	1.05	0.49	1.16		CLIENT	1.07	0.52	1.06
k(X)=17.44	SUPPL	1.00	0.45	1.10	k(X)=14.65	SUPPL	0.98	0.50	1.11
18)	S*E	4.62	0.85		**28)**	S*E	4.66	0.57	
N. of cases=99	R&D*E	0.54	1.41	1.16	N. of cases=556	R&D*E	0.41	1.16	1.10
	MACH*E	0.80	1.26	1.29		MACH*E	1.31	1.22	1.16
	EMPL	4.08	0.91	1.09		EMPL	3.99	0.89	1.15
	RMIXPROD	-0.56	0.72	1.07		RMIXPROD	-0.67	0.60	1.06
	CLIENT	1.05	0.50	1.07		CLIENT	1.09	0.46	1.09
k(X)=16.24	SUPPL	1.07	0.38	1.11	k(X)=17.32	SUPPL	1.01	0.42	1.11
19)	S*E	4.85	0.59		**29)**	S*E	4.83	0.55	
N. of cases=240	R&D*E	0.39	1.13	1.05	N. of cases=1449	R&D*E	0.82	1.14	1.04
	MACH*E	1.12	1.12	1.14		MACH*E	0.93	1.20	1.16
	EMPL	3.99	0.75	1.04		EMPL	4.25	1.03	1.13
	RMIXPROD	-0.48	0.47	1.01		RMIXPROD	-0.35	0.48	1.02
	CLIENT	1.10	0.48	1.09		CLIENT	1.19	0.39	1.04
k(X)=19.14	SUPPL	1.03	0.41	1.03	k(X)=15.95	SUPPL	0.92	0.45	1.05
20)	S*E	4.86	0.48		**30)**	S*E	4.85	0.64	
N. of cases=88	R&D*E	0.09	1.22	1.16	N. of cases=43	R&D*E	1.82	1.20	1.24
	MACH*E	1.31	1.20	1.21		MACH*E	1.26	1.02	1.31
	EMPL	4.01	0.80	1.22		EMPL	4.32	1.51	1.12
	RMIXPROD	-0.57	0.47	1.12		RMIXPROD	-0.30	0.51	1.36
	CLIENT	1.00	0.56	1.07		CLIENT	1.23	0.27	1.41
k(X)=19.49	SUPPL	1.06	0.41	1.04	k(X)=20.60	SUPPL	0.85	0.47	1.44
21)	S*E	5.07	0.40		**31)**	S*E	4.80	0.51	
N. of cases=85	R&D*E	0.39	1.36	1.49	N. of cases=372	R&D*E	0.77	1.38	1.07
	MACH*E	1.39	1.27	1.60		MACH*E	0.93	1.14	1.11
	EMPL	4.54	1.21	1.34		EMPL	4.48	1.18	1.03
	RMIXPROD	-0.82	0.69	1.09		RMIXPROD	-0.40	0.47	1.05
	CLIENT	1.06	0.52	1.14		CLIENT	1.16	0.40	1.03
k(X)=16.97	SUPPL	1.10	0.43	1.13	k(X)=15.26	SUPPL	0.97	0.41	1.02
22)	S*E	4.71	0.84		**32)**	S*E	4.64	0.62	
N. of cases=72	R&D*E	0.25	1.57	1.11	N. of cases=171	R&D*E	1.39	1.20	1.25
	MACH*E	1.56	1.23	1.18		MACH*E	1.04	1.18	1.11
	EMPL	4.00	1.02	1.35		EMPL	4.69	1.46	1.05
	RMIXPROD	-0.87	0.85	1.06		RMIXPROD	-0.40	0.45	1.22
	CLIENT	1.04	0.52	1.12		CLIENT	1.11	0.50	1.24
k(X)=18.29	SUPPL	1.11	0.37	1.01	k(X)=12.61	SUPPL	1.02	0.38	1.19
23)	S*E	6.77	1.40		**33)**	S*E	4.65	0.46	
N. of cases=28	R&D*E	0.54	1.43	1.43	N. of cases=272	R&D*E	1.43	1.18	1.08
	MACH*E	1.33	1.74	2.09		MACH*E	0.80	1.08	1.09
	EMPL	5.35	1.74	1.26		EMPL	4.05	0.99	1.08
	RMIXPROD	-0.47	0.36	1.90		RMIXPROD	-0.33	0.51	1.17
	CLIENT	0.85	0.51	1.04		CLIENT	1.20	0.35	1.06
k(X)=11.46	SUPPL	0.89	0.44	1.28	k(X)=16.29	SUPPL	0.95	0.40	1.10
24)	S*E	5.27	0.58		**34)**	S*E	4.72	0.51	
N. of cases=398	R&D*E	1.29	1.15	1.11	N. of cases=194	R&D*E	0.63	1.03	1.05
	MACH*E	1.31	1.44	1.06		MACH*E	0.96	1.31	1.08
	EMPL	4.94	1.29	1.07		EMPL	4.94	1.35	1.13
	RMIXPROD	-0.41	0.46	1.03		RMIXPROD	-0.50	0.58	1.06
	CLIENT	1.00	0.49	1.06		CLIENT	1.05	0.48	1.10
k(X)=14.19	SUPPL	0.91	0.43	1.08	k(X)=12.76	SUPPL	1.00	0.38	1.12
25)	S*E	4.91	0.45		**35)**	S*E	4.63	0.61	
N. of cases=258	R&D*E	0.46	1.18	1.08	N. of cases=95	R&D*E	1.07	1.38	1.06
	MACH*E	1.28	1.17	1.21		MACH*E	0.78	1.28	1.11
	EMPL	4.45	0.94	1.18		EMPL	5.04	1.68	1.19
	RMIXPROD	-0.62	0.56	1.04		RMIXPROD	-0.35	0.45	1.06
	CLIENT	1.09	0.48	1.12		CLIENT	1.03	0.47	1.10
k(X)=14.90	SUPPL	0.99	0.44	1.09	k(X)=11.88	SUPPL	0.87	0.44	1.05