DRUID

DRUID Working Paper No. 05-08

Services Innovation and Economic Performance: An analysis at the firm level

By

Luisa Ferreira Lopes and Manuel Mira Dodinho

Danish Research Unit for Industrial Dynamics

www.druid.dk

Services Innovation and Economic Performance: An analysis at the firm level

Luísa Ferreira Lopes

DCSA/FCT/UNL and IET/FCT/UNL
Lisbon, Portugal
E-mail: lflopes@fct.unl.pt

Manuel Mira Godinho

ESIG/UTL and CISEP
Lisbon, Portugal
E-mail: mgodinho@iseg.utl.pt

Abstract:
We present a model that links innovation effort to economic performance, along the lines of the Crépon et al (1998) model. However, in contrast to Crépon et al, that analyze R&D intensive manufacturing sectors, the present application examines the relationship between innovation and performance for services sectors. This is relevant since much effort has been made to explore that relationship for manufacturing but very little is known about it in the case of services sectors.
In trying to fulfill this gap the paper uses firm-level data from the Second Community Innovation Survey to estimate a simultaneous equations model for firms in ten services sectors in Portugal.
The present model also differs from former approaches by the specific explanatory structure proposed to estimate the complex relationship between innovation and economic performance. Instead of estimating a direct link between innovation and labor productivity, three specific relationships were put forward. The first of them explains the innovation effort intensity (an input in the innovation process). The second one relates service innovation (an output of the innovation process) to effort intensity and to other explanatory variables. Finally, the third relationship links labor productivity to both service innovation and effort intensity considering also some other influences.
Sensitivity analysis of the results to alternative estimation techniques was performed.

Key words: Innovation and performance; Innovation in services; Technology; Service sectors; Labor productivity; CIS

JEL Codes: O31, O33, L8

ISBN 87-7873-172-0

DRUID

Acknowledgements:
We thank Observatório da Ciência e do Ensino Superior (OCES) for giving access to services CIS2 data for Portugal, and the DRUID Winter Conference, 27-29 January 2005, for comments and suggestions. The usual disclaimer applies.

1 Introduction

In the section on future directions of their paper, Bartelsman & Doms point that:

> "A disproportionate amount of research has focused on the manufacturing sector. The lack of attention to non-manufacturing arises mostly because of difficulties in defining output and measures of inputs. (...) As the share of employment in manufacturing continues to decrease, the need for understanding productivity outside of manufacturing will become even more imperative." (Bartelsman & Doms, 2000, p.591).

Since then, not very significant progress has been done in the services context, as we shall see in the next section. In order to contribute to fulfill this gap, the goal of this paper is to provide new evidence on the innovation–productivity relationship in the services context, following the lines of Crépon et al (1998) that only analyze manufacturing sectors.

The model of Crépon et al provides a structural explanation of the R&D–productivity link and, at the same time, accounts simultaneously for two econometric problems: selectivity and endogeneity. In this paper, instead of concentrating on R&D (which is not much significant in the services context) we consider a more wide measure of innovation input: the investment in a set of innovation activities.

The model consists of a system of three simultaneous equations: the first one explains innovation effort intensity (an input to the innovation process). The second one relates service innovation (an output of the innovation process) to effort intensity. Finally, the third relationship links labor productivity both to service innovation and to effort intensity (considering that innovation activities may affect productivity directly and indirectly, through innovation output). In each relation, we consider a set of common determinants and some idiosyncratic ones. A feedback effect of innovation output on innovation input is introduced.

The model is estimated using Portuguese firm level data from the Second Community Innovation Survey.

As other services innovation studies use a single equation specification, a similar separate estimation of the equations of the model is also presented.

Furthermore, the present work differs from former approaches, in the services context, in two aspects: the way the innovation–productivity relationship is modeled and the econometric estimation methods.

The paper is structured in the following way: after a brief review, in section 2, of the most directly relevant literature, the model is presented in section 3 and the data set is described in section 4. In section 5 the results are presented and discussed and finally section 6 summarizes the conclusions.

2 Review of the Literature

Empirical innovation studies have, until recently, focused almost exclusively on manufacturing industries. This has been so, not because any restriction exists at the theoretical level. In fact, microeconomic theory says nothing about the distinction between manufacturing and services. There are firms, markets and market structures. In principle, what is said about firm behavior applies to a services firm as well as to a manufacturing one. The distinction between manufacturing and services has its origin in the economic activities classification for national accounting and statistical purposes. But when the topic of innovation, and previously the more restricted domain of Research & Development (R&D), was empirically investigated only manufacturing industries were included in the analysis. The reason is obvious: R&D and even the more wide concept of technological innovation are more visible in the manufacturing firms. Implicitly services activities were seen as independent of technology, although nothing was really stated explicitly about it.

This situation stayed unquestioned until the mid 1980's when the Information and Communication Technologies (ICT) began to diffuse rapidly, first in the financial sectors (Barras, 1986a, 1986b, 1990) and then spread to virtually every industry. Since then, services activities started to be a separate object of economic investigation from a technological and innovation perspective (they were already individually studied in management science and sociology, for instance). At the same time, the ever increasing weight of services in product and employment at the national level, in the more developed economies, points to a structural change in these economies. This fact made even more acute the need to empirically study services activities.

The increased attention in this area revealed that innovation took other forms besides technology (organizational, design). In a first moment these were considered as particular characteristics of services that required a different approach from the one used in manufacturing (Sirilli & Evangelista, 1998; Djellal & Gallouj, 1999; Preissl, 2000; Sundbo & Gallouj, 2000). This is still the object of much debate but some more recent perspectives (e.g. Howells, 2001; Miles, 2001) point to a continuum of characteristics that apply both to services and manufacturing, with each industry having its own combination of characteristics, without a clear separation between services and manufacturing.

In fact, services studies have called attention to aspects not exclusive of services but also relevant in the manufacturing domain, that were kept unnoticed only because they are less visible than strictly technological aspects, more obvious in manufacturing contexts.

The integration of services and manufacturing is a trend that seems to be increasing.

Nevertheless, the usual empirical difficulties of measurement are, in general, even more serious in services industries (as pointed by Bartelsman & Doms, 2000, and Coombs & Miles, 2000). That is the reason why the large majority of services studies use descriptive methods, a common characteristic of areas of investigation that are still in their early stages of development. Descriptive analysis is obviously valuable and it is through it that clues might be found for more rigorous approaches. However, these difficulties should not be an argument for not trying to use quantitative methods. Even with the severe limitations imposed by the available data, these tentative steps seem very useful because they reveal directions for further qualitative inquiry and, in this interaction, we hope, progress can be made.

As far as we know, only two such works have been done, so far, relating innovation to productivity, both very recent: Cainelli et al (2003) and Conceição et al (2003).

The first one has services as its exclusive object of study and combines information from the CIS2 survey with other complementary data in order to build a panel for Italy. The model has two equations, estimated independently, to account for a feedback effect between innovation and productivity. The problem of selection bias is taken into account but the possibility of endogeneity is not considered. The distinction between process and product/service innovation is introduced. The occurrence of an innovation and the expenditure in innovation activities are considered alternative measures and are introduced in the model one at a time.[1] Labor productivity is taken in levels but sales growth rates are also used. The study concludes with a positive relation between innovation and productivity level and also a virtuous reinforcement feedback mechanism.

The second study analyses both the manufacturing and services sectors. Different specifications are estimated with the combined sample. A model in growth rates is estimated for the two sub-sets separatly. The data comes from the CIS2 for Portugal, and for some other countries for a part of the study. The endogeneity problem is accounted for but not selection bias, because it is considered that the inclusion in the data set of firms that have attempted to innovate solves the problem, at least partially. This is not our point of view. The selection bias may yet be present in the data, since we can not exclude that the probability of an innovating firm answering an innovation survey may be significantly different from the probability of a noninnovating firm answering the same questionnaire.

The relationship between innovation and productivity is modeled with a single equation. A second equation is estimated for innovation but only as part of a Two Steps Instrumental Variables approach to deal with the endogeneity problem. The study concludes with a positive relation between innovation and the level of productivity but finds a negative impact of innovation on productivity growth.

The model of Crépont et al (1998) has had many different implementations with several variants differing in the data used, in the choice of explanatory variables and in the estimation method.[2] But all of them are R&D oriented and only include manufacturing industries in the data set. Both the selectivity and the endogeneity problems are accounted for. Mairesse & Mohnen (2003) use CIS II data for France, Spain, Germany and the United Kingdom, agregated at the industry level, to estimate a version of this model. Only R&D intensive firms are considered. The study concludes with a positive relation between product innovation and the level of productivity but finds no evidence of a significant impact of process innovations on productivity.

[1] In this paper we follow a different modeling approach: as the occurrence of an innovation is an output of the innovation process and the financial effort in innovation activities is an input, we do not consider appropriate to take both as substitutes.

[2] For a survey of this model's implementations see Mairesse & Mohnen (2003).

3 The Model: Definition of Variables and Econometric Model Specification and Estimation

The empirical model we propose consists of three equations: one for innovation input, one for innovation output and one for labor productivity.

The variables used are defined in Table 1.

Table 1: List of Variables

Variable Name	**Variable Code**	**Proxy**	**Type**
Effort Intensity	effort	total expenditure in innovation activities in 1997 per employee	censored, log, thousand escudos
Service Innovation	inser	introduced an innovation in the period 1995/1997	binary
Labor Productivity	prod	turnover per employee in 1997	log, thousand escudos
Cooperation	coop		binary
Demand Pull	Dpull	set of objectives linked with demand, with an average score of moderate or very important	binary
Cost Push	Cpush	set of objectives linked with cost reduction, with an average score of moderate or very important	binary
Information from clients	Icli	moderate or very important source of information	binary
Information from consultants	Icon	moderate or very important source of information	binary
Information from suppliers	Isup	moderate or very important source of information	binary
Size	emp	number of employees	count
Group Belonging	gb		binary
New Firm	nf		binary
Share of exports	turnexp	share of turnover exported	percentage
Share of qualified workers	empq	share of workforce highly qualified	percentage
Government Support	gs		binary
Industry effects	I_i	10 industries	dummy
Regional effects	R_i	7 regions	dummy

3.1 Innovation Input Equations

As innovation input (to the innovation process) we consider a measure of "Innovation Effort". The *proxy* used is the level of total expenditure in innovation activities in 1997, which includes R&D as part of the full set of innovation activities. These activities are identified in Table 2.

Table 2: Innovation Activities

Code	**Activity**
RRDIN	Internal R&D
RRDEX	External R&D
RMAC	Machinery Acquisition
ROET	SW and other Technology Acquisition
RPRE	Preparation Activities
RTR	Training
RMAR	Market Introduction

Innovation effort is a dependent censored variable because we only observe the "Innovation Effort" if the firm reports that it is engaged in innovation activities, although we also observe the independent variables otherwise. We are interested in explaining the "Innovation Effort" but we also have observations on firms that don't perform innovation activities.[3]This censoring results from the firms decisions and not from the way the data was collected.

In this situation, it is assumed that there is an unobserved latent variable S_i^*, for the firm i, which compares to a threshold value (censoring or selection criteria) above which a firm will engage in innovation activities. In other words, S_i^* expresses some decision criteria (such as the expected present value of the firm profit accruing to innovation investment — Crépon et al, 1998) for a firm to make an "Innovation Effort". This unobserved latent variable has an observed censored counterpart, in our case the level of total expenditure in innovation activities in 1997.

So, first, the model has a selection equation, accounting for the fact that we observe that the firm is engaged in innovation activities. This criterion function, determining the censoring, is of the Probit type (Maddala, 1983).

The dependent variable in this equation is a dummy variable — the selection variable S_i — that takes value 1 if S_i^* is positive or larger than some constant threshold (industry specific provided industry dummies are included in X_{1i}) and, in this case, we observe that the firm has engaged in innovation activities. S_i will be 0 otherwise:

$$\begin{cases} S_i = 1 & \text{if } S_i^* \equiv X_{1i}\beta_1 + u_{1i} > 0 \\ S_i = 0 & \text{otherwise} \end{cases} \tag{1}$$

where X_{1i} is a vector of explanatory variables, β_1 is the associated coefficient vector and u_{1i} an error term.

Then, the second equation explains the level or intensity of the innovation effort, when $S_i = 1$, that is when S_i^* is larger than the industry threshold. Only for the selected observations — those firms that have decided to perform innovation activities — is the

[3]In a truncated model we would only observe the regressors and the dependent variable if the firm reports that it is engaged in innovation activities. In such case, we would only observe firms that perform innovation activities (Maddala, 1990).

magnitude of these activities investigated:

$$\begin{cases} \mathsf{effort}_i = X_{2i}\beta_2 + u_{2i} & \text{if } S_i = 1 \\ \mathsf{effort}_i = 0 & \text{otherwise} \end{cases} \tag{2}$$

where effort_i is expressed in logarithms, X_{2i} is a vector of explanatory variables, β_2 is the associated coefficient vector and u_{2i} a disturbance term that summarizes omitted determinants and other sources of unobserved heterogeneity.

Finally, the two equations form a Generalized Tobit II Model,[4] because effort_i is only observable when S_i^* is larger than the industry threshold and we assume the joint normality of the bivariate distribution of u_{1i} and u_{2i}, in order to have an estimable model.

The Tobit II model is also referred to as the *Sample Selection Model* in the context of a sample selection bias or selectivity bias (Verbeek, 2000, p.207).[5] This problem arises if the probability of a particular observation to be included in the sample depends upon the phenomenon we are explaining.

And this may be a potentially serious problem in our particular situation (Crépon et al, 1998; Mairesse & Mohnen, 2003; Cainelli et al, 2003). In fact, nonresponses may result in a selection bias because the probability of an innovating firm answering a survey on innovation is larger than the probability of a non innovating firm answering the same survey — we will have an innovator selection bias. The same argument can be applied to justify an effort selection bias.

3.2 Innovation Output Equation

As innovation output (of the innovation process) we use the information of whether the firm reports that it has introduced in the market any service or service production/supplying method technologically new or improved, during the period from 1995 to 1997, or not.

This measure does not give an indication of magnitude of the results obtained from the innovation process. It would be better if we had data on the number of innovations, but we only have information on the occurrence of innovations in the period 1995–1997. We don't know if the firm has introduced 1 or 100 innovations. Even better would be a measure of the value of the benefits obtained from those innovations.

But of course, we are restricted in the choice of indicators by the survey questionnaire which is even more restrictive in the case of services. In particular, the usual distinction between process and product innovation was not introduced in the services questionnaire.

In manufacturing studies, the most used indicators for innovation output, particularly for product innovation (Mairesse & Mohnen, 2003), are number of patents and share of innovative sales. But these cannot be used in this case. The patent count, although available, is not a good indicator of the results from the innovation process in service firms. In fact, only 1% of the firms reported that they had registered at least one patent in the

[4]This classification of Tobit models is due to Amemiya (1984) (see Verbeek, 2000, p.207).

[5]Sample selection is also called *incidental truncation* (Green, 2000, p.926).

period 1995–1997. The share of innovative sales could be a good indicator.[6] Unfortunately, only the manufacturing firms were asked to report this value.

This equation explains a dichotomous variable inser_i indicating whether the firm has introduced an innovation of any kind during the previous three years, or not:[7]

$$\begin{cases} \mathsf{inser}_i = 1 & \text{if } \mathsf{inser}_i^* = X_{3i}\beta_3 + u_{31} > 0 \\ \mathsf{inser}_i = 0 & \text{otherwise} \end{cases} \tag{3}$$

where X_{3i} is a vector of explanatory variables, β_3 is the associated coefficient vector and u_{3i} a disturbance term.

This is a Probit model, where u_{3i} follows a standard normal distribution.

It should be noted that this equation is included not just for the sake of solving the endogeneity problem (as in Conceição et al, 2003),[8] but as a structural relationship of interest *per se*. We are interested in explaining the behavior of firms concerning the determinants of innovation output, in particular the fact that a firm is able to introduce an innovation.

3.3 Labor Productivity Equation

The economic performance indicator used is labor productivity, measured as turnover per employee (gross output divided by labor).

Of course, it would be better if we had value added per employee or total factor productivity (TFP). But, in the absence of data on value added and capital stock, this is a way to approximate the behavior of productivity (Mairesse & Mohnen, 2003; Conceição et al, 2003; Cainelli et al, 2003).

This equation explains the behavior of labor productivity (considering the influence of innovation while controlling for other influences)

$$\mathsf{prod}_i = X_{4i}\beta_4 + u_{4i} \tag{4}$$

where prod_i is expressed in logarithms, X_{4i} is a vector of explanatory variables, β_4 is the associated coefficient vector and u_{4i} is a disturbance term following a standard normal distribution.

This equation is specified in a loglinear form in order to reduce the heteroscedasticity problem .

3.4 The System of Equations

Taken together, the Innovation Effort equations, the Services Innovation equation and the Labor Productivity equation form a nonlinear system of simultaneous equations.

[6] Particularly if it is reported as an interval variable (Crépon et al, 1998) in order to reduce the potential errors in estimating this value.

[7] A similar variable is used for process innovation by Mairesse & Mohnen (2003).

[8] Anyway, the use of Instrumental Variables is not the best way of addressing the endogeneity problem when there is heteroscedasticity in the data, as is the case in the CIS2 database.

The interdependence nature of the economic relations is a major characteristic of the innovation process and cannot be ignored, neither from an economic nor from an econometric point of view, and requires a simultaneous equations system estimator (as already pointed out by Crépont et al, 1998, and Mairesse & Mohnen, 2003).[9] In fact, in a system of equations, the simultaneous nature of the relations expresses the interaction between the variables in the model.

From an econometric point of view this characteristic introduces an endogeneity problem in a single equation model (for instance between innovation output and productivity): when the disturbance term changes, the endogenous variable, it determines directly, changes; this, in turn, changes all the other endogenous variables since they are determined simultaneously; this means that the endogenous variables used as regressors are contemporaneously correlated with the disturbance term in that equation. In these circumstances the OLS estimator is inconsistent (it is not centered even asymptotically) and cannot be used.

To estimate a system of equations one can choose from two different approaches: a limited information method (which estimates each equation in the system separately) or a full information method (which estimates all the equations as a hole). We choused to follow the full information approach although these methods have the problem of a misspecification in one of the equations contaminate the estimation of the rest of the equations (even if they are correctly specified). We decided to use this approach because it uses all the available information to estimate each of the parameters and so produces more asymptotically efficient estimators.

From the set of full information estimators we have chosen the Generalized Method of Moments (henceforth GMM) because it is more efficient in the presence of heteroscedasticity in conjunction with endogeneity and the computational cost of GMM no longer is an argument against this method.

Table 3 summarizes the structure of the model.

We allow for a feedback effect of innovation output on innovation input. As innovation output is measured by the occurrence of a service innovation in the period 1995–1997 and innovation input is measured as expenditures in innovation activities at the end of the period, in 1997, it seems reasonable to consider this approach.

Since we had no *a priori* reasons to do otherwise, the vector of explanatory variables is the same for the two equations of the Tobit model for innovation effort, in other words, the factors that determine the decision of investing in innovation activities are the same that explain the magnitude of the investment.

One major problem resulting from the cross-section nature of this study is the fact that the output of the innovation process is the result of past efforts and we only have the level of contemporaneous effort.

[9] This has not been, to our knowledge, fully taken into account in prior services studies (Cainelli et al, 2003; and Conceição et al, 2003).

Table 3: Model Specification

Explanatory Variables	Effort Selection X_1	Effort Intensity X_2	Service Innovation X_3	Labor Productivity X_4
Effort Intensity			$\surd$	$\surd$
Service Innovation	$\surd$	$\surd$		$\surd$
Cooperation	$\surd$	$\surd$	$\surd$	
Demand Pull[1]	$\surd$	$\surd$	$\surd$	
Cost Push[2]	$\surd$	$\surd$	$\surd$	
Information from clients	$\surd$	$\surd$	$\surd$	
Information from consultants	$\surd$	$\surd$	$\surd$	
Information from suppliers	$\surd$	$\surd$	$\surd$	
Size	$\surd$	$\surd$	$\surd$	$\surd$
Group Belonging	$\surd$	$\surd$	$\surd$	$\surd$
New Firm	$\surd$	$\surd$	$\surd$	$\surd$
Share of Exports	$\surd$	$\surd$	$\surd$	$\surd$
Share of qualified workers	$\surd$	$\surd$	$\surd$	$\surd$
Government Support	$\surd$	$\surd$	$\surd$	$\surd$
Industry effects	$\surd$	$\surd$	$\surd$	$\surd$
Regional effects	$\surd$	$\surd$	$\surd$	$\surd$

Notes: [1] Demand pull is a dichotomous variable that takes the value one when, on average, the firm gave a score greater than 2 (very or moderately important) to the set of four objectives "replace products being phased out", "improving service quality", "extend service range" and "open new markets or increase market share". [2] Cost push is a dichotomous variable that takes the value one when, on average, the firm gave a score greater than 2 (very or moderately important) to the set of two objectives "improve process flexibility" and "reduce labor costs".

4 The Data Set

The data set used comes from the Portuguese "Second Community Innovation Survey". In Portugal this survey was conducted in the second half of 1998 by *Observatório das Ciências e das Tecnologias (OCT)*, under the supervision of EUROSTAT. Firms were asked to answer questions relating to the 1995–1997 period (Conceição & Ávila, 2001).

The service industries included in the data set are identified in Table 4. The firms in the sample belong to seven different Portuguese regions.

The population of the services sectors under study had 6311 firms, including all those with at least ten employees. The initial sample drawn from this population had 2444 firms and the final sample 1017 firms (Conceição & Ávila, 2001, p.17).

The data file supplied by OCES only had 1014 observations (firms), with the original values, unweighted. The sample was stratified by NACE code (at 5 digits level) and size (6 size classes by number of employees: 10-19, 20-49, 50-99, 100-249, 250-499, 500 and over). A set of 246 weights, one for each stratum, was also provided in order to obtain a weighted sample.

From the 1014 initial observations 5 were deleted due to inconsistencies. Hence, the sample used had 1009 valid observations. Missing values for explanatory variables regarding innovators were considered as zero responses. Table 5 presents information about the data

Table 4: Services Sectors (by NACE code, Rev. 1)

NACE	Sector Name
51	Wholesale Trade
60	Land Transport
61	Sea Transport
62	Air Transport
642	Telecommunications

NACE	Sector Name
65	Banking
66	Insurance
67	Other Financial Services
72	Computing and Software
742	Engineering

set and in Table 6 are indicated some descriptive statistics about the variables used.

There is a high level of heterogeneity, between the ten sectors in the sample, concerning the innovative behavior of firms, as we can see in Table 5.

Table 5: Sample Description

Service Sectors	Total	51	60	61	62	642	65	66	67	72	742
Number of firms	1009	365	287	6	8	13	121	34	25	58	92
Firms engaged in innovation activities	.25	.11	.24	.00	.13	.62	.31	.47	.44	.66	.29
Firms that innovated	.24	.12	.22	.00	.25	.54	.34	.47	.48	.64	.25
Firms engaged in R&.D	.13	.05	.05	.00	.13	.77	.21	.41	.24	.52	.16
Firms that cooperated	.08	.03	.04	.00	.00	.31	.15	.18	.16	.28	.10
Firms that received government support	.04	.01	.07	.00	.13	.15	.02	.00	.00	.14	.03
Firms that have patented	.01	.00	.01	.00	.00	.00	.01	.00	.04	.10	.01

5 Results

5.1 Simultaneous Equations System

The results of the estimation of the model with GMM, as a simultaneous equation's system, with all the explanatory variables (including the statistically insignificant ones) are presented in Table 7.

Preliminary tests confirmed de presence of heteroscedasticity (White and Breush-Pagan Tests) and endogeneity (Wu-Hausman Test after a Reset2 and a Reset3 Tests revealed no evidence of relevant omitted variables). Therefore, we have perform heteroscedastic-robust estimations.

Industry dummies and region dummies are introduced in all the equations as control variables and we will not report on them.

Innovation effort intensity has an obviously expected positive and significant effect on innovation output. If firms spend more on innovation activities they have a higher probability of introducing a service innovation. Anyway, a causality relationship cannot

Table 6: Descriptive Statistics

Variable	Mean	Standard Deviation
Effort Intensity (log)	-7.956	8.078
Service Innovation	0.241	0.428
Labor Productivity (log)	9.858	1.087
Cooperation	0.079	0.270
Demand Pull	0.052	0.221
Cost Push	0.133	0.339
Information from clients	0.174	0.380
Information from consultants	0.097	0.296
Information from suppliers	0.170	0.376
Size (log)	3.461	1.088
Group Belonging	0.277	0.447
New Firm	0.025	0.156
Share of Exports	0.053	0.154
Share of qualified workers	0.157	0.231
Government Support	0.039	0.193

be established because we are not controlling the time dimension. The direct impact of this variable on labor productivity is also positive and statistically very significant. This would suggest that the innovation activities, undertaken in order to develop and implement service innovations, are *per se* a source of more labor efficiency.[10]

The feedback effect of innovation output on innovation input is positive and very significant, which is consistent with the results of Cainelli et al (2003).

The estimated effect of innovation output on labor productivity is very large but negative. This is in contradiction with most of the literature. Conceição et al (2003) found a negative relation but with productivity growth and not with productivity level. This is an intriguing result and we still do not have a satisfactory explanation for it.

From the set of innovation input and innovation output common determinants (cooperation, demand pull, cost push, and sources of information) only the information from suppliers is significant. We observe a very large negative effect on innovation investment and a positive, although not very significant (it is not significant at 5%), effect on innovation output. This is another quite intriguing result. A possible explanation is that firms do not pay for information from suppliers but, nevertheless, they do have a positive role in the introduction of innovations in the market (for example the case of suppliers of information technologies). And, even more, this free information apparently makes it unnecessary to

[10]But, again, caution should be taken in this interpretation, because we are measuring labor productivity with turnover per employee, not value added.

make larger innovation investments.

Size is a control variable and, as expected, has a relevant role although in an unexpected way. In fact it has a positive impact on innovation output but a large negative effect on innovation effort intensity and no impact on labor productivity. Larger firms would innovate more than smaller ones with less effort (i.e. they are more efficient in innovation activities). But this result should be interpreted with caution, especially because of the time dimension that is not included in this analysis. In fact, bigger firms (for instance banks) may have had large innovation investments in the past (we are only measuring effort in 1997) and are now implementing the resulting service innovations (during the period 1995–1997).

Group belonging only affects the labor productivity and has a significant positive effect on this variable. This result would suggest that group firms tend to be more efficient than independent ones but that they do not have a significantly larger engagement in innovative activities.

Being a new firm, exposition to international competition, and the share of qualified workers doesn't have any significant statistical impact in any of the dependent variables.

Also, government support does not have a significant effect neither on the effort intensity nor on innovation output or even on labor productivity. This may seem a surprising result but in the services context government support is less frequent than in the manufacturing context. In our sample only 4% of the firms report having received government support.

5.2 Independent Equations

As other services innovation studies use a single equation specification,[11] a separate estimation of the equations of the model was rehearsed.

Innovation effort was estimated as an independent Tobit and innovation services as an independent Probit. The labor productivity equation was estimated by the Instrumental Variables (IV) approach through a two steps procedure.

We observe that the results — presented in Table 8 — change dramatically.

Effort intensity still has a significant (slightly smaller) positive effect on innovation output but the coefficient's sign in the labor productivity equation changed and is highly negative. A much similar situation is observed for the innovation output variable: the effect on effort intensity, although much smaller in magnitude, retains the same sign but the effect on labor productivity is now positive and very high. It should be noted, though, that in spite of the statistical significance of the coefficient (at a 5% significance level) the estimate is highly inaccurate (it has a very high standard error).

From the previously significant variables two are no longer significant (size in the service innovation equation and group belonging in the productivity equation), two maintain the sign but the magnitude of the coefficient changes (information from suppliers in the service innovation equation and size in the effort intensity equation), and one changes the sign

[11]Cainelli at al (2003) use a system of two equations (estimated separately) but just for modeling a feedback effect between innovation and productivity, not to deal with endogeneity.

and is now positive.

Another remarkable change is the large number of other variables that turn to be significant when the model is estimated separately. In fact, cooperation, information from clients and share of exports are now highly significant in at least one of the equations where they are included. And cost push, group belonging and government support are also significant, although only at a 10% significance level.

This sensitivity of the results to a different estimation method is a clear indication that it is critical to carefully consider the econometric characteristics of the estimation procedure in connection to the data characteristics and to the relations to be tested.[12]

[12]For instance, the non robustness of the Probit and the Tobit estimators to heteroscedasticity and nonnormality of the residuals 'shows that data censoring can be very costly' (Wooldridge, 2002, p.533).

Table 7: System Estimation with GMM

Explanatory variables	**effort intensity**	**service innovation**	**labor productivity**
Effort Intensity		0.3994 (0.0364) **[.017]**	0.0869 (0.0056) **[.000]**
Service Innovation	25.3075 (3.9946) **[.000]**		-2.3149 (0.7778) **[.003]**
Cooperation	0.7035 (2.3596) [.766]	-0.0301 (0.0957) [.753]	
Demand Pull	-0.4994 (2.7394) [.855]	0.1906 (0.1118) [.865]	
Cost Push	-1.7363 (2.2467) [.440]	0.0670 (0.0906) [.459]	
Information from clients	-3.1193 (2.6207) [.234]	0.1229 (0.0924) [.184]	
Information from consultants	-1.5240 (2.3276) [.513]	0.0595 (0.0928) [.521]	
Information from suppliers	-6.5685 (2.8893) **[.023]**	0.2630 (0.1356) [*.053*]	
Size	-1.5054 (0.4727) **[.001]**	0.0605 (0.0242) **[.013]**	-0.0820 (0.0766) [.285]
Group Belonging	1.2846 (1.2278) [.295]	-0.0523 (0.0533) [.327]	0.4817 (0.1503) **[.001]**
New Firm	-1.8920 (2.2042) [.391]	0.0766 (0.0910) [.400]	-0.0994 (0.2563) [.698]
Share of exports	-1.4710 (2.9140) [.614]	0.0613 (0.1187) [.606]	-0.0084 (0.3408) [.980]
Share of qualified workers	-2.6160 (1.6519) [.113]	0.1055 (0.0714) [.140]	-0.3498 (0.2144) [.103]
Government Support	34.8469 (23.8844) [.145]	-1.4246 (1.0847) [.189]	3.1660 (2.0122) [.116]

All regressions include industry and region dummies. Estimated with TSP 4.5 . Standard errors, heteroscedastic-robust, inside ( ). P–values inside [ ].

Table 8: Separate Estimation

Explanatory variables	**effort intensity**	**service innovation**	**labor productivity**
Effort Intensity		0.1096 (0.0116) **[.000]**	-1.1107 (0.5020) **[.027]**
Service Innovation	6.7365 (0.4880) **[.000]**		26.2346 (12.0240) **[.029]**
Cooperation	1.6294 (0.4500) **[.000]**	0.0956 (0.3010) [.751]	
Demand Pull	-0.5675 (0.5467) [.299]	0.2368 (0.4666) [.612]	
Cost Push	0.8260 (0.4305) [*.055*]	0.4243 (0.2411) [*.078*]	
Information from clients	2.1400 (0.3925) **[.000]**	0.7754 (0.1990) **[.000]**	
Information from consultants	0.3072 (0.4491) [.494]	0.4209 (0.2771) [.129]	
Information from suppliers	2.2397 (0.4313) **[.000]**	0.9205 (0.2211) **[.000]**	
Size	-0.5135 (0.1433) **[.000]**	0.1337 (0.0824) [.105]	-1.1625 (0.5795) **[.045]**
Group Belonging	0.7513 (0.4042) [*.063*]	-0.0063 (0.2153) [.976]	0.4546 (0.4852) [.349]
New Firm	-0.1118 (0.8822) [.899]	0.4131 (0.5561) [.458]	-0.6411 (0.6730) [.341]
Share of exports	2.0020 (0.9283) **[.031]**	-0.5935 (0.5323) [.265]	1.8632 (1.4963) [.213]
Share of qualified workers	1.0277 (0.6989) [.141]	0.4429 (0.3632) [.223]	-1.2142 (1.0074) [.228]
Government Support	0.3347 (0.5786) [.563]		-3.9356 (2.3628) [*.096*]

All regressions include industry and region dummies. Estimated with TSP 4.5 . Standard errors, heteroscedastic-robust, inside ( ). P–values inside [ ].

6 Conclusions

In this paper we have tried to model the relationship between innovation and economic performance, in the services sectores context, using new data on innovation in service industries and also exploring alternative approaches to previous research in this area. Instead of establishing a simple direct link between innovation and labor productivity, we have taken into account not only the result of the innovation process but also the activities prior to the market introduction of the innovation, allowing for a direct and an indirect effect (through innovation output) of this variable on labor productivity. Our work indicates that this may be a relevant determinant of productivity.

We have also tried to deal with the many econometric problems of this economic relationship and this data. That effort is still in progress. The most relevant limitation of this investigation is its pure cross-section nature as innovation is intrinsically a dynamic process. As already mentioned, the data set also imposed some significant limitations to the proxies that could be used for innovation output and for productivity.

Estimating the three relationships as a system gives a negative impact of innovation output on productivity and a positive impact of effort intensity. Estimating the equations separately gives a positive and very large effect of innovation output on productivity and a negative effect of innovation intensity. This unexpected result leads us to conclude that the econometric methods used are of crucial importance in this context and that particular care must be taken in this respect (including evaluating, in the specific data context, the validity of the hypothesis implied by the estimation methods) in order to have confidence in the results one gets from the empirical estimation of models. As a consequence, this paper is a tentative step to use more rigorous quantitative methods (limited by available data) and an exploratory work pointing to further investigation.

The great sensitivity of the results to different specifications and different estimation methods clearly indicates the need for further investigation in this area. It is still not clear actually which type of specification and estimation method should be preferred. The specific characteristics of the data (heteroscedasticity, endogeneity, selectivity and censoring) require particular care with the econometric methods used.

Of course, an immediate development of this work will be to introduce the critical time dimention by using panel data (combining CIS II data with the results of CIS III) to implement a dynamic model that can better describe the relationships between innovation input, innovation output and labor productivity of firms.

Another possible future improvement is to break the sample in two sub-samples, according to the intensity of the innovation behavior of the sector's firms. The previous analysis would then be made over a group of highly innovative sectors and over another group of low innovative sectors. Although the present analysis accounts for idiosyncrasies in different sectors (through the inclusion of sector dummies) the nature of the relationships of interest may be structurally diverse between firms in sectors that present a significantly different attitude towards innovation.

Finally, it should be stressed that the data used comes from a survey that simply enlarges the scope of the universe under study to services industries, without taking into consideration the specific characteristics of innovative activities in these sectors (Gallouj & Weinstein, 1997). This is a difficult but very significant problem that needs to be addressed in the future.

References

Barras, Richard (1986a), 'Towards a theory of innovation in services', *Research Policy*, V.15, N.4, pp.161–173

Barras, Richard (1986b), 'New Technology and New Services: Towards an innovation strategy for Europe', *Futures*, V.18, N.6, pp.748–772

Barras, Richard (1990), 'Interactive innovation in financial and business services: The vanguard of the service revolution', *Research Policy*, V.19, N.3, pp.215–237

Bartelsman, Eric & Mark Doms (2000), 'Understanding Productivity: Lessons from Longitudinal Microdata', *Journal of Economic Literature*, V.38, N.3, pp.569–594

Cainelli, Giulio, Rinaldo Evangelista & Maria Savona (2003), 'The impact of innovation on firm's growth and productivity in Italian services', Paper presented at the International Workshop "Empirical Studies on Innovation in Europe", Urbino, Italy, mimeo

Conceição, Pedro & Patrícia Ávila (2001), *A Inovação em Portugal: II Inquérito Comunitário às Actividades de Inovação*, Celta Editora, Oeiras, Portugal

Conceição, Pedro, Manuel Heitor & Francisco Veloso (2003), 'Innovative Shocks and Productivity', Paper presented at the Conference in Honour of Keith Pavitt "What do we Know about Innovation", Brighton, UK, mimeo

Coombs, Rod & Ian Miles (2000), 'Innovation Measurement and Services: The New Problematic', in J. Stanley Metcalfe & Ian Miles, eds., *Innovation Systems in the Service Economy: Measurement and Case Study Analysis*, Kluwer, London, UK, pp.85–103

Crépon, Bruno, Emmanuel Duguet & Jacques Mairesse (1998), 'Research, Innovation and Productivity: An Econometric Analysis at the Firm Level', National Bureau of Economic Research, Working Paper 6696, http://www.nber.org/papers/w6696

Djellal, Faridah & Faïz Gallouj (1999), 'Services and the search for relevant innovation indicators: a review of national and international surveys', *Science and Public Policy*, V.26, N.4, pp.218–232

Gallouj, Faïz & Olivier Weinstein (1997), 'Innovation in Services', *Research Policy*, V.26, N.4-5, pp.537–556

Green, William (2000), *Econometric Analysis, 4th ed.*, Prentice Hall, New Jersey, USA

Howells, Jeremy (2001), 'The Nature of Innovation in Services', *Innovation and Productivity in Services*, OECD, Paris, France, pp.55–79

Maddala, G. S. (1983), *Limited-dependent and qualitative variables in econometrics*, Econometric Society Monographs N.3, Cambridge University Press, Cambridge, MA, USA

Maddala, G. S. (1990), 'Censored Data Models', in John Eatwell, Murray Milgate & Peter Newman, eds., *The New Palgrave: Econometrics*, Macmillan, London, UK, pp.54–57

Mairesse, Jacques & Pierre Mohnen (2003), 'R&D and Productivity: A Reexamination in Light of the Innovation Surveys', Paper presented at the DRUID Summer Conference 2003, Copenhagen, Denmark, mimeo

Miles, Ian (2001), 'Services Innovation: A Reconfiguration of Innovation Studies', PREST Discussion Paper 01-05, Manchester, UK

Preissl, Brigitte (2000), 'Services Innovation: What Makes it Different? Empirical Evidence from Germany', in J. Stanley Metcalfe & Ian Miles, eds., *Innovation Systems in the Service Economy: Measurement and Case Study Analysis*, Kluwer, London, UK, pp.124–148

Sirilli, Giorgio & Rinaldo Evangelista (1998), 'Technological innovation in services and manufacturing: results from Italian surveys', *Research Policy*, V.27, N.9, pp.881–899

Sundbo, Jon & Faïz Gallouj (2000), 'Innovation as a loosely coupled system in services', *International Journal of Services Technology and Management*, V.1, N.1, pp.15–36

Verbeek, Marno (2000), *A Guide to Modern Econometrics*, John Wiley & Sons, Chichester, UK

Wooldridge, Jeffrey (2002), *Econometric Analysis of Cross Section and Panel Data*, MIT Press, Cambridge, MA, USA