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Incentives and uncertainty: an empirical analysis of the impact of demand on innovation

Roberto Fontana and Marco Guerzoni*

We study the impact of demand on innovation. By focusing on a sample of smalland medium-sized enterprises in several industries and European countries, we analyse how demand stimulates innovation by providing economic incentives and reducing uncertainty. Considering the size of the market as a proxy for the presence of demand, we find support for the idea that the presence of incentives stimulates innovation. This is particularly true for process innovation. In considering interaction with customers as a way to reduce uncertainty, we find that firms that see customers as the most important sources of information for both innovation ideas and completion, tend to introduce product innovations. Firm size, R&D expenditure and sectoral effects also matter.

Key words: Demand, Product innovation, Process innovation, Market size *JEL classifications*: O31, O33

1. Introduction

There is an extensive literature on the influence of demand upon innovation. According to this literature, demand can influence firms' innovative choices in two ways. On the one hand, there is the '*incentive effect*', according to which, once an innovation is introduced in the market, demand acts as a multiplier of the increased firm mark-up. Schmookler (1962) suggests that, the larger the market, the stronger is the impact of this effect, and that it favours process innovations. On the other hand, there is an '*uncertainty effect*'. This effect impinges upon the assumption that introducing new or radical products and forecasting their pace of adoption are difficult, due to the intrinsic uncertainties associated with novelty. Within this context, demand can pull innovation by 'channelling' to firms useful knowledge about markets' need. By reducing firms' uncertainty about expected profits, knowledge can stimulate innovation. This effect was first highlighted by Myers and

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Marquis (1969) and was studied further by von Hippel (1978) and, more recently, by other scholars (Herstatt and von Hippel, 1992; Morrison *et al.*, 2000). Despite the presence of a rich literature on these effects, most of contributions provide only limited empirical support for their existence. Indeed, their presence has been strongly questioned (see, among others, Kleinknecht and Verspagen, 1990; Mowery and Rosenberg, 1979) on the grounds that the conceptualisation of demand is not clear, the mechanism at work is not always specified and the causality flow is often spurious.

In this paper we suggest that the paucity of empirical support may derive from two reasons. First, it can be argued that it is difficult to observe a clear-cut distinction between the two effects. Both effects might be at work conjunctly and might be difficult to disentangle. Second, it must be acknowledged that these effects impinge upon firms' choices in different ways and any empirical test should take this into account. We present an empirical analysis of the influence of demand on product and process innovations, which attempts to differentiate between these two effects. In particular, we study their joint impact on firms' propensity to innovate, for a cross-section of innovative firms in Europe. Data are from a survey of small and medium-sized enterprises (SMEs) that was carried out in 2000 and covers seven EU countries (Denmark, France, Germany, Greece, Italy, the Netherlands and the UK) and five sectors: food and beverages, chemicals (excluding pharmaceuticals), communications equipment, telecommunications services and computer services (Caloghirou *et al.*, 2006).

We first analyse the literature on the relationship between demand and innovation and discuss its achievements and main limits. Second we discuss the information collected in the survey relevant to our understanding of the relationship between demand and innovation. Finally, we use an econometric model to account for the influence of economic incentives and uncertainty on both firms' propensities to innovate and the direction of their innovative efforts. Analysis of the joint effect of these mechanisms is the first original contribution of the paper. It should also be noted that these demand-related effects may not impact homogeneously across firms. By controlling for sectoral level specificities and firm level heterogeneity our analysis will provide suggestions about the micro characteristics that are relevant to asses the impact of economic incentives and uncertainty on the propensity to innovate.

The paper is organised as follows. Section 2 reviews the background literature and introduces the main hypotheses. Section 3 presents the data and describes the variables and the econometric model. Section 4 presents the main findings and Section 5 concludes.

2. Background literature and hypotheses

Analysis of the influence of demand on innovation dates back to the 1960s, when Schmookler (1962, 1966) and Myers and Marquis (1969) highlighted the excessive emphasis given to technology as a major source of innovation. Schmookler (1962: 1) in fact stated that 'New goods and new techniques are unlikely to appear, and to enter the life of society without a pre-existing—albeit possibly only latent—demand.' Both Schmookler and Myers and Marquis focused on the role of demand, but addressed the issue from different perspectives. Schmookler saw demand as a source of economic incentive for invention. He argued that the evolution of an economic activity, which was an invention, will be driven by expected profitability. And, in particular, if an improvement in production

technique or product quality results in a higher mark-up per unit, then the higher the number of units sold, the greater will be the value of the future stream of profits. If we take the size of the market as a proxy for expected demand, the incentives to innovate should be positively correlated with the size of the market.

In terms of the analysis we assume a binary variable y_t , taking the value 1 if the firm is innovating and 0 if it is not, and assume that the probability P_t of a firm that is innovating at time t depends on an information set Ω_t :

$$P_t \equiv \Pr(y_t = 1 \mid \Omega_t) = E(y_t \mid \Omega_t) \tag{1}$$

Schmookler assumed that the information set required to predict y_t consisted of the incentives generated by the expected profit Π_t . Thus,

$$P_t \equiv E\left(y_{t|} \mid \Omega_t\right) = F\left(\Pi_t\right) \tag{2}$$

where F is a transformation function defining the Cumulative Density Function of a probability distribution.¹ At a given point in time, firm *i*'s profit can be then written as:

$$\Pi_i = (p - c)x_i - E \tag{3}$$

where p is the price of a product, c is its marginal cost of production, x_i is the quantity sold by the firm and E is the fixed costs of invention. If S is the total expenditure in a sector, the firm's market share can be defined as:

$$s_i = \frac{p \, x_i}{S} \tag{4}$$

and equation (3) then becomes

$$\Pi_i = (k \, s_i) \, S - E_i, \text{ with } k = \left(1 - \frac{c}{p}\right) \tag{5}$$

and, ceteris paribus:

$$P_t \equiv E(y_t \mid \Omega_t) = F(S_t) \tag{6}$$

Thus, the larger the size of the market, S, the bigger will be the firm's expected profits, and the incentives for and the likelihood of innovating.

However, this line of reasoning only holds under two assumptions. First, that an innovation should have no effect on either total market expenditure or firm's market share. Second, that the fixed costs of invention are spread uniformly across firms. These implicit assumptions have been highlighted in the literature. Scherer (1982), re-ran Schmookler's analysis and found lower coefficients for the significant, demand-related variables. This result was not surprising given that the expected size of the market did not always completely overlap with demand for the firm's product.

In his analysis Schmookler refers mainly to established industries within an oligopolistic market structure, and to innovation in existing products (Schmookler, 1966: 153) because, in these circumstances, the size of the actual market is a good proxy for expected sales. Scherer, on the other hand, used a broader data-set and included several types of industries showing that innovation could modify the market structure by providing a temporary monopoly or reduce profits by cannibalising existing products. A model that aims to take

¹ The usual assumptions hold:
$$F(-\infty)=0$$
, $F(\infty)=1$, and $f(\Pi_t)=\frac{\partial F(\Pi_t)}{\partial \Pi_t}>0$

account of the effect of market size on innovation, should assume an endogenous market structure. Analytical models of 'patent races' (Reinganum, 1989) and of endogenous market structures (Sutton, 1998) adopt this path. Kleinknecht and Verspagen (1990) used Schmookler's dataset for an empirical study that precisely highlighted the presence of reverse causality. If, on the one hand, the size of the market sets incentives for invention, it is also true that, on the other hand, an innovation has positive effect on the size of the market itself. This discussion suggests that Schmookler's intuition is valid, but would be more robust empirically if the above mentioned flaws were controlled for—and especially in those sectors where the size of the market is likely to remain stable. Some recent empirical research has focused on single sectors where controlling for market structure and reverse causality is easier. For instance, Lichtenberg and Waldfogel (2003) addressed the problem of incentives for pharmaceutical firms to invest in R&D into cures for rare diseases, while Popp (2002) explored the correlation between patents and energy prices in selected industries.

It should be noted that many studies that investigate the link between market size and innovation do not succeed in grasping the complexity of the innovation process. Indeed, innovation is often measured simply as level of R&D or number of patents, assuming a linear model of innovation, and with no attempt to distinguish between process and product innovation. However, there are some theoretical and empirical studies that have tackled this distinction in the innovation process.

Schmookler (1962) already intuited that a reduction in unit cost due to a process innovation is positively correlated with the level of output, but that this does not hold with the same intensity for product innovations. However, the first convincing analytical account of this effect came from Cohen and Klepper (1992, 1996A, 1996B) and Klepper (1996). Assuming precisely the mechanism suggested by Schmookler, they showed that increased demand created a greater incentive for the firm to engage in process rather than product innovation. Cohen and Klepper (1996B) successfully tested their theory in a sample of 587 firms from various sectors.

It should be noted that in these studies the effect of the market is relatively larger for process innovation, but expectations about a positive market share are also a necessary condition for product innovation. For instance, product innovation will serve new buyers (Klepper, 1996) and new submarkets (Klepper and Thompson, 2007) or yield profits via licensing (Klepper and Cohen, 1996B). When the expected gain in the market from product innovation is small, firms will rarely engage in any kind of innovation, as occurred, for instance, in the market for vaccines where pharmaceutical firms foresaw the impossibility of setting sufficient high prices for selling or licensing the drugs (Kremer *et al.*, 2006).

This attempt to capture the dualism in the incentive to innovate represents a remarkable step forward in the understanding of the differing nature of product and process innovation. However, there is a stream of literature that adds a further complexity. In addition to acknowledging the role of demand in providing economic incentives for innovation, Myers and Marquis (1969), Langrish *et al.* (1972) and other empirical studies (Berger, 1975; Boyden, 1976; Freeman, 1968; Isenson, 1969; Lionetta, 1977; National Science Foundation, 1959; Rothwell and Freeman, 1974) stress the crucial role of demand as a direct source of innovation. These works, based on information from questionnaires and interviews, tried to understand the technical and economic contexts in which innovation occurs. They found that, in most cases, innovative firms perceived demand to be the leading factor in successful innovation, in the sense that customers provided firms with knowledge such as new ideas or specific requirements. For this stream of literature, the probability of firms being innovative can be summarised as:

$$P_t \equiv E(y_t | \Omega_t) = F(I_t) \tag{7}$$

where the variable I is a proxy capturing firms' information on user needs. More and better information reduces uncertainty and increases the probability that the firm will introduce a successful innovation. The main weakness of this approach is the identification and meaning of variable I which, at least initially, was rather blurred. This point was made by Mowery and Rosenberg (1979) and Dosi (1982), who argued that the concept of demand as used by Myer and Marquis was too broad, vague and difficult to operationalise. According to Dosi: 'to conclude that it is demand that drives innovation, market must *clearly* be distinguished from the potentially limitless set of human needs' (Dosi, 1982: 150). Failure to do so, Dosi said, would lead to the 'incapability of defining the why and when of certain technological developments instead of others and of a certain timing instead of other' (Dosi, 1982: 150).

Von Hippel was the first author to respond to these criticisms by introducing the concept of 'lead users' defined as 'consumers whose present strong needs will become general in a marketplace months or years in the future' (von Hippel, 1986: 792). Since lead users are knowledgeable about how they could benefit significantly from the solution of a problem, they are both able and willing to interact with firms and are important sources of information. Along the same lines, Teubal (1979) suggests that the influence of demand upon innovation depends on 'need determinateness, the extent to which preferences are specified (or need satisfaction is expressed) in terms of product classes, functions and features' (Teubal, 1979, quoted in Clark, 1985: 244). Recently, von Tunzelmann and Wang (2003) introduced the concept of user capabilities (i.e. the ability to reap utility from an innovation). This ability depends on the users' capabilities in coupling their needs to the solution provided by the innovation (i.e. sophistication). Similarly Malerba *et al.* (2007) and Adner and Levinthal (2001) focused on the role of heterogeneity in customers' preferences as a source of innovation.

The concept of sophistication overturns the Mowery–Rosenberg–Dosi critique because demand is no longer considered as the 'potentially limitless set of human needs' but rather as a set of specific needs put forward by sophisticated users. As a consequence, Dosi's argument is turned upside down and demand becomes the source of information on which to base the selection of opportunities that actually fit with users' preferences, from the potentially limitless set of technological opportunities. In this case, the variable *I* is no longer conceived as a vague idea of demand, but rather as a proxy for those concrete interactions that actually take place between the firm and the sophisticated users (both customers and firms) it is producing for. As von Hippel (1982) proposes, the role of users is mostly successful either in the case that they suggest ideas for new product or even if they create prototypes.

In light of the above discussion, we can point to two different mechanisms underlying the way that demand acts on innovation.¹ On the one hand, demand is conceived as an incentive mechanism, which, as suggested above, will be relatively more intensive for process innovation where the expected size of the market is easier to forecast. On the other hand, introducing either new products or radical product improvements and forecasting

¹ As argued above, the relationship between demand and innovation is complex and variable and our framework does not capture all its facets. However, it does provide a useful starting point for analysing the different roles played by demand in different types of innovation, namely process and product innovation.

their pace of adoption is difficult due to the intrinsic uncertainties associated with novelty. According to this view, demand can trigger innovation by *reducing* uncertainty (i.e. by providing useful knowledge about market needs). In other words, by reducing uncertainty about expected profits, knowledge can stimulate innovation.

It is clear that information about users' requirements is relatively more necessary for developing products than for process innovations, which tend instead to impinge more upon the firm's technological knowledge base. Thus, not only are there two different demand-led mechanisms at work, but also each of them leads to a different type of innovative output. While the presence of these two effects has been discussed at length, their different impact on innovative output has rarely been empirically studied. This may be one reason why, after five decades, debate on the relationship between demand and innovation is still ongoing. Our analysis empirically addresses the dualism in both the underlying mechanism of the demand-pull hypothesis and the resulting outcomes.

In the remainder of the paper we tackle two issues. First, as in the previous literature, we test the presence of the two effects without differentiating between process and product innovation. Second, we provide evidence for the presence of different innovative outputs due to the alternative mechanisms underlying the effects.

First, we consider:

$$P_t \equiv E(y_t | \Omega_t) = F(S_t, I_t)$$
(8)

and test:

Hypothesis 1: The Schmookler Hypothesis. The size of the market (S) has a positive impact on the probability of the firm being innovative.

Hypothesis 2: The Myer and Marquis Hypothesis. The degree of interaction with users (I) has a positive impact on the probability of the firm being innovative.

Although we control for firm and sector heterogeneity in order to take account of the criticisms levelled by the literature, we do not expect a clear result in terms of statistical significance. Indeed, the way that our hypotheses are formulated does not allow for the different mechanisms underlying the two effects. The size of the market rarely has a positive impact on the probability of introducing new products and there may be no specific reasons why interactions with external partners (customers in particular) should help firms to develop cost-reducing process innovations.

In terms of the second issue we want to address, we note that innovative processes are complex and that incentive and uncertainty effects are likely to act simultaneously. Thus, it is problematic to neatly disentangle a 'pure' incentive effect from a 'pure' uncertainty effect. However, if both effects are present, then, in innovative firms, we should observe a relatively higher propensity for process innovation when the market size increases, and a relatively higher propensity for product innovation when interaction with users increases.

Analytically, we are interested in observing a new variable \bar{y} , which would take the value 0 if the firm pursues both process and product innovation, 1 if it focuses on product innovation and 2 if it focuses on process innovation:

$$P_t = E(\bar{y}| \ \Omega_t) = F(S_t, I_t) \tag{9}$$

Then, in comparing innovative choices, we should observe that a marginal increase in the interaction with users will have a positive impact on the likelihood of product innovation, while a marginal increase in market size positively affects the likelihood of undertaking process innovation.

Thus we test:

Hypothesis 3: Incentive effect. The size of the market stimulates process innovation rather than product innovation activity in innovative firms.

Hypothesis 4: Uncertainty effect. The degree of interaction with users stimulates innovative firms to undertake product rather than process innovation.

In the following sections of the paper we address each hypothesis in turn. If our findings reject these hypotheses, then we can conclude that, at least according to the perceptions of the firms in our sample, demand plays a minor role in innovation. If this is not the case, then we should find some support for our hypotheses or, at least, some of them.¹

3. Empirical analysis

We carry out the analysis on a cross-section of data from SMEs in seven EU countries (Denmark, France, Germany, Greece, Italy, The Netherlands and the UK) and five industries: food and beverages (NACE 15), chemical excluding pharmaceuticals (NACE 24 minus NACE 24.4), communication equipment (NACE 32), telecommunications service (NACE 64.2) and computer services (NACE 72). The information comes from a 2000 survey that targeted SMEs, with between 10 and 1,000 employees.² This survey is the European equivalent of the 'Carnegie Mellon Survey' on industrial R&D in the US manufacturing sector (described in Cohen *et al.*, 2002), and aimed at investigating the extent, implications and mechanisms of innovation-related knowledge flow in European industry. The questionnaire was in two parts. The first part aimed at obtaining general information on the respondents (i.e. innovativeness, collaborations with external partners, sources of information for innovative activity, etc.). The second part asked respondents to identify the 'most economically important innovation introduced by the firm in the most recent three years' and, related to this innovation, to answer a set of questions, (e.g. on the most important external contributors to the innovation, etc.).

Of the 587 firms surveyed, 558 were innovators and 447 were able to identify their most economically important innovation.³ These firms constitute our sample. Of these firms in the sample, 344 were 'particularly innovative' (i.e. they engaged in both product and process innovation). On average these firms introduced 15% of their new improved product and/or processes in collaboration with external partners. To shed some light on the relationship between innovativeness and the importance of reliance on external information sources, we split the sample of collaborating firms into those firms that relied more than average on external partners (144 or 32% of the sample) and those that did not. The data suggest that innovative firms in the food and beverages (28%) and computing services (27%) sectors generally rely more than average on external partnerships for innovation. Firms in the communication equipment (15%) and telecommunication services (10%) sectors displayed the lowest frequencies of participating, with chemical firms (20%) in between.

¹ This holds within the boundaries of the following important *caveat*. Process innovation can be considered a good proxy for the results of an incentive-led innovation process, while product innovation may be only weakly linked to the presence of the *uncertainty effect*.

² The KNOW survey was undertaken during a research project funded by the European Commission. Carried out in 2000 by means of Computer Aided Telephone Interviews (CATI) method; it refers to 1999. See Caloghirou *et al.* (2006), for a description of the survey's methodology and main results.

³ Forty firms in our sample were not able to identify their most economically important innovation. Fortythree did not indicate the year in which the most economically important innovation was carried out. Twentyeight firms gave incorrect answers indicating a year outside the proposed range.

To explore the relationship between innovativeness and demand, we look at the role of external sources of information on innovative firms. Of the 447 firms that were able to identify their most economically important innovation, 212 (or 47%) pointed to *customers* as the most important source of information for both innovation ideas and innovation completion, suggesting that interaction with customers is particularly important for innovation. The importance of reliance on customers varies across sectors. While for some 25% of firms in the computer services, chemicals, and food and beverages sectors customer interaction is the most important source of innovation, the percentage is considerably lower for firms in the telecommunication services and communication equipment sectors (9% and 15% of respondents, respectively).

A further breakdown of these data by most important innovation *type* is represented in Figure 1. In our sample 188 firms identified a 'product innovation' as their most important innovation; 64 identified a 'process innovation' and 195 pointed to a 'combined product/ process or service innovation'. This distribution suggests a relatively higher importance of customers for firms involved in 'combined product/process or service innovation' compared to other types of innovation, across all sectors except telecommunication services and communication equipment. Among those sectors whose most important innovation was a 'product innovation', communication equipment and computer services (followed by food and beverages) put the most importance on customers. As expected, the distribution of responses among firms whose most important innovation was a 'process innovation' was much lower. Of these, chemical firms relied relatively more on customers.

Finally, we consider the relationship between market size and type of most important innovation. One question in the survey asked firms to report total revenues in the most recent fiscal year. We used this information to construct a measure of aggregate market size, aggregating revenues by sector and by country.¹ We constructed four market size categories: the small market size (up to \in 340,000), which includes 108 firms (24% of the sample); medium–small market size (between €341,000 and €680,000), which includes 114 firms (25%); medium-large market size category (between €681,000 and €1.12 million), which includes 108 firms (24%); and large market size (more than \in 1.12 million), which includes 117 firms (27%). Figure 2 depicts the percentages of respondents that identified their most important innovation by market size and type of innovation. Results indicate that a relatively large share (31%) of firms operating in medium-small markets consider product innovation to be most important economically. Firms involved in 'combined product/process or service innovation' activity are more evenly distributed across market sizes, although the largest share of firms involved in this type of innovation was in the medium-large market category. Of particular interest for our purposes is the case of process innovation where the percentages suggest that the majority (56%) of firms that consider 'process innovation' as being most important economically, operate in large and medium-large markets.

Again there is heterogeneity across sectors. In Figure 3 we plot the percentages of respondents that identified their most important innovation as being a 'process' innovation, by market size and sector of activity.² It is interesting to note that for food and beverages and computing services the majority of firms involved in process innovation

¹ Thirty-six firms that identified their most important innovation did not answer this question. We imputed to these cases the average revenues calculated for the sector and the countries to which the firms belonged.

² All the telecommunication services firms in our sample fall into the first category. For this reason we do not report them in this figure.

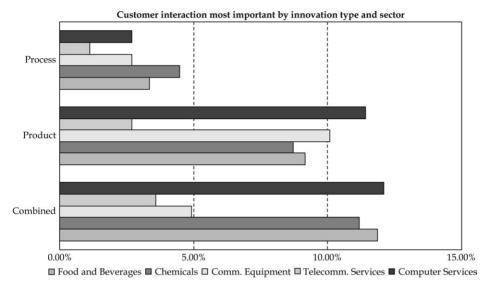


Fig. 1. Customer interaction most important by innovation type and sector.

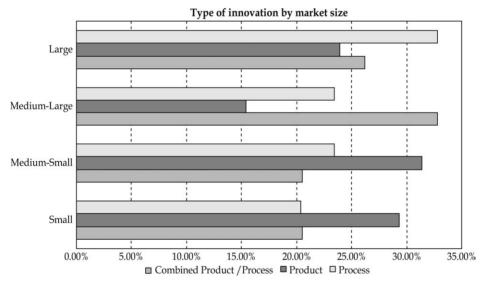


Fig. 2. Most important innovation by market size.

operate in medium-large or large markets. The distribution of chemical firms is more uniform across the four categories with most firms concentrated in the middle categories, while firms in communication equipment are concentrated in the medium-small category.

Overall, these descriptive statistics provide some preliminary support for our hypotheses. Innovative firms generally tend to collaborate more with external partners, which are a valuable source of external information. Customers seem to be the most important source of information for firms engaged in product innovation—for both innovation ideas and innovation completion. Market size is positively associated to innovation, particularly for firms conducting process innovation. On the basis of this preliminary evidence, we

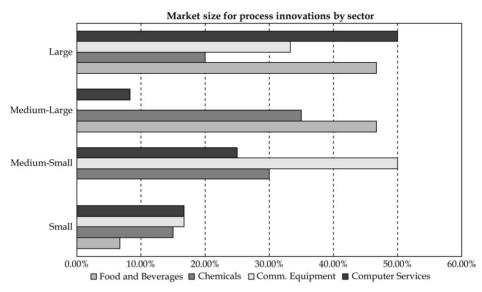


Fig. 3. Market size for process innovation by sector.

conducted two additional types of analysis. First, we investigated the determinants of innovative activity, focusing on firms involved in both process and product innovation. This was intended as a response to Hypotheses 1 and 2. Second, we focused on firms' most economically important innovations and examined the determinants of product innovation *compared with* process or other types of innovation. This analysis was intended to provide evidence on the roles of uncertainty and the incentives underlying innovation, and was aimed at supporting or disproving Hypotheses 3 and 4.

3.1 Econometric analysis

To test our hypotheses, we needed to estimate two equations. In the case of Hypotheses 1 and 2 we relied on additional information from the survey. In our sample 362 firms reported having done process innovation (in the 3 years preceding the survey) and 429 reported having introduced a new or improved product. Most of these firms (344) had engaged in both types of innovation. We focused on just these firms, which were particularly innovative. The variable NEW PROC & NEW PROD was 1 if respondents that identified their economically most important innovation also reported engagement in both product and process innovation and 0 if they reported only one or other type of innovation. For these firms, we estimated a binary Probit model. We assumed that for each firm, i, there was an observable variable such that:

$$y = 1 \quad if \quad y_i^* > 0$$

$$y = 0 \quad if \quad otherwise$$
(10)

where we defined y_i^* as

$$y_i^* = \beta' X_i + \varepsilon_i \tag{11}$$

where X is the vector of explanatory variables, β is the vector of coefficients and ε_i is a normally distributed error term.

To test Hypotheses 3 and 4, we focused on the responses to the questions in the second part of the survey. As already mentioned, the second part of the questionnaire asked firms to focus on 'the most economically important innovation introduced in the most recent three years'. Of the 447 firms that identified an innovation, 188 referred to it as a 'product innovation', 64 identified it as a 'process innovation' and 195 as a 'combined product/ process or service innovation'. We considered the firms' responses as the outcome of a choice among three alternatives: j = 0, combined product/ process or service innovation; j = 1, product innovation; j = 2, process innovation. We modelled the choice with the following multinomial logit equation in which X is the vector of covariates:

$$\Pr(y_i = j) = \frac{e^{\beta_j X_i}}{\sum\limits_{k=0}^{2} e^{\beta_k X_i}}$$
(12)

which is normalised as follows (Greene, 2003: 860):

$$\Pr(y_i = j) = \frac{e^{\beta_j X_i}}{1 + \sum_{k=1}^{j} e^{\beta_k X_i}} \quad for \quad \mathcal{J} = 1, 2$$

and
$$\Pr(y_i = 0) = \frac{1}{1 + \sum_{k=1}^{j} e^{\beta_k X_i}}$$
(13)

Before describing our results we needed to clarify an econometric issue related to the (potential) presence in our analysis of a selection bias, which could have arisen if we had excluded from the analysis firms that did not identify their most important innovation. To overcome this potential bias, we adopted a two-step estimation model similar to the Heckman (1979) procedure for selection bias. We first estimated a binary model.¹ In this case the dependent variable was equal to 1 if the firm identified its most economically important innovation, and 0 otherwise. The chosen covariates were a set of explanatory variables available for all the firms in the sample (i.e. both those that identified their most important innovation and those that did not).² Second, we used the residuals from this regression to construct the inverse Mills ratio, which was introduced as an additional covariate in the second stage.³

³ In the case of Hypotheses 1 and 2, this procedure produces efficient and consistent estimates of the unknown coefficients of the equations. In the case of Hypotheses 3 and 4, this procedure deviates from the two-step standard Heckman procedure in the sense that the effects of sample selection do not follow the traditional (simple linear) approach (van de Ven and van Praag, 1981; Dubin and Rivers, 1989). Thus, standard errors for the estimated multinominal logistic coefficients are not adjusted. We produce adjusted standard errors via boostrapping. In other words, we resampled with replacement from the whole sample and repeated the procedure 2000 times to obtain different estimates of the parameters from which the correct standard errors were calculated.

¹ When we test Hypotheses 1 and 2, we estimate a probit model in the first stage. When we test Hypotheses 3 and 4, we estimate a logit model.

² The covariates used in the first stage are: R&D, EMP, HEADQ and the set of country dummies. To ensure some variability between the two steps of the model, country dummies are excluded from the second stage and new variables such as EXT INTER, NO OF COMPETITORS (see below) and industry dummies are added.

3.2 Explanatory variables

Our explanatory variables include indicators for market size and importance of customers as a source of information for innovation, as well as a set of controls for firm size, R&D activity, firm status and industry-related dummies. In terms of market size, the discussion in Section 2 stresses that firms facing a large market may have higher incentives to innovate. Indeed, central to Schmookler's argument is the role of innovation as a driving force underlying the increase in price margins induced by a decrease in production costs, especially in the case of process innovation. Based on the fact that price margin is positively linked to market power, some of the studies in the literature use related indicators, such as firms' market shares. Indeed, Link (1982) found that among more R&D intensive industries the share of R&D dedicated to process innovation increased with market concentration. There are several indicators of market concentration in the literature (see Sakakibara and Porter, 2001, for a review of their various strengths and weaknesses). We do not have information on firms' market shares, which prevents us from constructing sensible indicators of market concentration. However, we do have information on total revenues. The variable MKT SIZE is the total calculated by revenues, by sector, by country, for the firms in our sample. We expected this variable to impact positively on the probability to innovate (Hypothesis 1) and on the likelihood of process innovation being undertaken(Hypothesis 3), especially when compared with the likelihood of product innovation.

On demand as a source of knowledge for new ideas and/or specific requirements, there is a bourgeoning literature on the impact of incoming spillovers on innovation as well as on the importance of external channels of information as sources of innovation ideas (Laursen and Salter, 2006). The second part of the questionnaire, which focused on the most economically important innovation, asked firms to select the most important contributor to both innovation completion and innovation ideas, from a list of possible candidates (Competitors, Suppliers, Customers, Universities and PROs, Consultants). CUST INTER is a dummy that equals 1 for firms that selected customers as the most important contributors to both innovation idea and innovation completion, and 0 otherwise. This is an indicator of customer involvement in the innovative process, which was used to test Hypotheses 2 and 4.

Alongside these variables that we used to test our main hypotheses, we controlled for additional determinants of innovative activity. The first was intensity of competition. Brouwer and Kleinknecht (1996) argue that in open economies characterised by the presence of small firms, the share of SMEs in a sector is an indicator of the intensity of competition. Given that we do not have information on firms' market shares, we use the number of firms competing in the same market as the indicator. No OF COMPETITORS is the log of the number of competitors in the main business, according to the survey respondents. Then we included another measure of interaction. In the first part of the questionnaire, firms were asked to state the percentage of new or improved production processes or products introduced in collaboration with external partners.¹ EXT INTER is the simple mean of the percentage of both improved products and processes introduced in collaboration with external partners.

¹ In both cases the exact wording of the question(s) was: 'What percentage of your firm's new or improved production processes (products) were introduced using any of the following methods: buying-in; in-house development; collaboration with external partners.'

Additional control variables were chosen following Czarnitzki and Kraft (2004), who also worked on the KNOW dataset. First, we considered whether the firm performs R&D. R&D is a dummy equal to 1 if the firm engages in this activity and 0 if not.¹ The positive link between R&D activity and innovativeness at firm level has been studied at length. The empirical evidence supporting this positive relationship has been explained in terms of the expertise necessary to identify and apply relevant external knowledge i.e. 'absorptive capacity' (Cohen and Levinthal, 1990). Consistent with these findings we expect firms that perform continuous R&D to be more likely to carry out product and process innovation. Second, we account for firm size. Again, there are several contributions that support the influence of firm size on innovativeness. Freeman and Soete (1997) found that larger firms were mainly responsible for process innovation in the chemical sector in the late nineteenth and twentieth centuries. Pavitt et al. (1987) found that for larger firms generally the share of innovative effort devoted to process innovation was greater. More recent analyses point to the presence of a mainly positive relationship between firm size and the composition of R&D activities. In a sample of manufacturing firms Scherer (1991) found that process R&D increased relative to product R&D as the size of the firm increased. Cohen and Klepper (1996B) qualify Scherer's results. They measured process R&D as the share of process patents over total patenting effort and firm size in terms of unit sales. They found that process share increased with size, but at a declining rate. Our proxy for firm size was the number of employees divided by 1,000 (EMP). We expected this variable to be positively related to innovativeness and to significantly affect the impact of the probability of conducting process innovation compared with product innovation. Third, we accounted for firm status. Concentration of R&D activity at the firm's headquarters has been found to positively impact on innovation (Mohnen and Hoareau, 2003). HEADQ is a dummy that is equal to 1 if the respondent was located at the company, headquarters and 0 if he/she was located in a division or a subsidiary. We expected headquarters location to be positively associated to both product and process innovation.

We controlled for sector fixed effects by introducing a set of industry dummies. Indeed, innovative characteristics are sector specific (Malerba, 2002) and can be assumed to derive from differences in technological characteristics (Pavitt, 1984), opportunities and appropriability regimes (Levin *et al.*, 1987). These variables should account for the impact of organisational structure and market conditions on the type of innovation. Finally, we included a full vector of country dummies to account for country fixed effects. This vector is included in the selection equation. Descriptive statistics for the variables are reported in Table 1. The correlation matrix is contained in the Appendix.

4. Results

Table 2 reports the results of heteroskedastic robust estimations. Column 1 shows the results of the selection equation. Column 2 reports the estimates for the second stage probit. In this case, the results show that the larger the size of the market, the more likely firms were to perform both product and process innovation, as suggested by the positive and significant coefficient of MKT SIZE. The coefficient of CUST INTER was also positive, but not significant. Concerning our control variables, the coefficient of EXT INTER was positive and significant, suggesting that firms that collaborate with external partners were more

¹ Information on R&D expenditure is available. It is not included in the regression due to correlation with firm size.

Table 1. Summary descriptive statistics

Variable name	Observed	Mean	SD	Min	Max
Selection	558	0.80	0.40	0:111	1:447
NEW PROC & NEW PROD	435	0.78	0.41	0:91	1:344
Most important innovation	518	0.73	0.72	0	2
EXT INTER (%)	483	0.15	0.19	0	100
MKT SIZE ($\times 10^3$ Euros)	518	11.73	12.32	0.091	44,495
NO OF COMPETITORS (log)	519	2.54	1.32	0	8.517
CUST INTER	558	0.41	0.50	0:233	1:325
EMP ($\times 10^3$)	558	0.88	0.32	0	1
R&D	558	0.19	0.26	0:64	1:494
HEADQ	554	0.56	0.50	0:241	1:313
Food and beverages	558	0.24	0.42	0:426	1:132
Chemicals	558	0.24	0.42	0:426	1:132
Communciations equipment	558	0.18	0.38	0:457	1:101
Telecommunication services	558	0.09	0.28	0:510	1:48
Computer services	558	0.26	0.44	0:413	1:145

For dummy variables, the last two columns report the number of cases in which the variables take the value 0 or 1.

	Dependent variable						
Independent variable	(1) Selection	(2) NEW PROC & NEW PROD					
CUST INTER		0.046 [0.145]					
MKT SIZE		0.011 0.006]*					
NO OF COMPETITORS		-0.028 0.061					
EXT INTER		0.809 0.405 **					
R&D	0.079 [0.316]	0.601 0.216 ***					
EMP	1.099 [0.290]***	1.034 [0.373]***					
HEADQ	0.044 [0.146]	-0.389 [0.159]**					
ρ		0.880 [0.341]**					
Country dummies	Yes	No					
Industry dummies	No	Yes					
Total observations	486						
Censored observations	109						
Uncensored observations	377						
Log pseudo LL	-356.862						
Wald χ^2	41.53						

 Table 2. Determinants of innovative activity: probit regression with sample selection. Dependent variable: NEW PROC & NEW PROD

*10% significance level; **5% significance level; ***1% significance level. Robust standard errors in parentheses.

likely to introduce both new products and new processes. Firms that perform R&D had a relatively high probability of being innovative, as indicated by the positive and highly significant coefficient for R&D. Also, size matters, as suggested by the positive and

significant coefficient of EMP, meaning that larger firms had a higher probability of being particularly innovative. This result still held if we used only the number of employees engaged in R&D. The coefficient of HEADQ was negative and significant, indicating that divisions and/or delocalised subsidiaries were more likely to do both product and process innovation than headquarters.¹ Finally, the selection variable (ρ) was statistically significant. This is an indication of the need to control for sample selection bias. Altogether these results seem to provide partial support for our hypotheses. Our findings tend to support Hypothesis 1 (the 'Schmookler hypothesis') in the sense that market size does significantly impact on innovation, thus Hypothesis 2 (the 'Myer and Marquis' hypothesis) was rejected.

To probe this evidence further, we turned to the results of the estimation of our second model, which contrasted the probabilities of carrying out different types of innovation. As mentioned in the previous section, in this case we first estimated a logit regression and used the residuals from this estimation to construct the inverse Mills ratio, which was introduced as an additional covariate in the second stage multinomial logit regression. Results and bootstrapped standard errors are reported in Table 3.

In Table 3, the first column contrasts the choices of firms whose most economically important innovation was a product innovation, with those of firms whose most economically important innovation was a service or a combined product/process innovation. With respect to our previous results, there were some interesting differences. CUST INTER, our proxy for the 'uncertainty effect', was still not significant. However, MKT SIZE, as measured by total industry revenues for the firms in our sample, was negative and significant, indicating that the larger the market size, the lower the probability of product innovation being the most economically important type of innovation. EXT INTER was negative and significant indicating that firms engaged in product innovation tend to collaborate relatively less with external partners. The coefficient for R&D was positive and significant, as expected, while the estimate for EMP was not significant, thus suggesting that size does not seem to significantly affect the probability of product innovation being the most economically important innovation compared to service or product/process innovation. It was interesting to note that firm status, proxied by HEADQ, was positive and significant, indicating that respondents located in the firm's headquarters, as opposed to being in a subsidiary or another division, tended to be relatively more likely to engage in product innovation.

The second column in Table 2 contrasts the choice of process innovation as the most economically important innovation, with the probability of combined product/process innovation. What is interesting here is that the coefficient of CUST INTER is negative and significant, which indicates that firms that considered customers to be the most important source of information for both innovation completion and innovation ideas were relatively less likely to engage in process innovation as compared with combined product/process innovation. Our indicator for firm status (HEADQ) was still positive, although less significant than in the previous regression.

The results in the last column of Table 2 are the most interesting. Here, we contrast the probability of engaging in process innovation with the probability of conducting product innovation as the most economically important innovation. In this column the coefficients

¹ Coefficients for industry dummies in the second stage equation are generally not significant and, for clarity, not reported in Table 2.

	(3)	(4)	(5)		
	[1 versus 0]	[2 versus 0]	[2 versus 1]		
CUST INTER	-0.093 [0.245]	-1.065 [0.340]***	-0.973 [0.349]***		
MKT SIZE	-0.041 [0.012]***	-0.014 [0.015]	0.027 [0.016]*		
NO OF COMPETITORS	-0.132 [0.101]	0.138 [0.138]	0.270 [0.130]**		
EXT INTER	-1.884 [0.701]***	-1.089 [0.830]	0.795 [0.925]		
R&D	1.114 [0.443]**	0.696 [1.297]	-0.418 [1.297]		
EMP	-0.535 [0.492]	0.241 [0.553]	0.775 [0.624]		
HEADQ	0.684 [0.265]**	0.527 [0.327]*	-0.157 [0.352]		
Mills ratio	-0.197 [0.491]	-0.101 [0.599]	0.096 [0.593]		
Industry dummies	Yes				
Observations	428				
LR χ^2 (26)	137.63***				
Pseudo R ²	0.146				
Log pseudo LL	-401.392				
IIA	-0.856	-1.320			
Combined	53.485***	43.933***	56.111***		

Table 3. Comparing innovation types: multinomial logit regression. Dependent variable: mostimportant innovation

*10% significance level; **5% significance level; ***1% significance level. IIA, independence of irrelevant alternatives. Bootstrapped standard errors in parentheses (2,000 iterations).

j = 0, Other (i.e. combined, service innovation); j = 1, Product innovation; j = 2, Process innovation.

are the difference between those in the second and first columns. An increase in the coefficient of the explanatory variable increased the probability of process innovation if the estimated coefficient of process innovation was higher than the corresponding coefficient of product innovation. In this case, the result for CUST INTER confirms the previous one. Firms that valued customers as the most important source of innovation for both innovation ideas and innovation completion were relatively less likely to undertake process innovation than product innovation as their most economically important innovation. In addition, the coefficient of MKT SIZE was now positive and significant, indicating that the probability of process innovation being the most economically important innovation tended to be higher the larger the size of the market in which the firm was operating. This result is reinforced by the coefficient of NO OF COMPETITORS, which was also positive and significant. The last row in Table 2 reports the results of two tests. The IIA (Independence of Irrelevant Alternatives) test checked whether the three alternatives considered (i.e. doing product innovation, doing process innovation, doing combined product/process innovation or service innovation) were indeed independent. The results confirmed the assumption that they are independent. The combined likelihood ratio test rejected the null hypothesis that each category could be merged with the other two.

Demand could play one of two roles in the process of innovation. It could act as a 'monetary mechanism' by providing incentives through large market size or it could lower the uncertainty associated with innovation outcomes. These two mechanisms have different impacts on the innovative output: the incentive effect tends to favour process innovations, while the uncertainty effect tends to 'pull' product innovations. Overall, our

results suggest that if we do not account for the type of innovation, the empirical support is only partial, as shown by our first regression. To reveal the two mechanisms described above, we propose a model in which product and process innovations are considered separately. In this case, our results confirm the hypothesis that market size favours process innovation compared with product innovation. Also, the evidence that customer interaction increases the likelihood of observing product innovation is significant, albeit weakly so. Due to the complexity of the innovation process, neat estimation of the impact of the two effects is problematic and we cannot precisely assess the return on innovation from the increase in market size and/or interaction with users. However, we can conclude that, depending on which effect prevails, demand directs firms' innovative activity towards process or product innovation.

5. Conclusions

This paper has presented an empirical analysis of the influence of demand upon product and process innovations. The innovation literature generally points to two effects of demand on innovation. On the one hand, demand provides an economic incentive to firms that want to innovate. If an improvement in production techniques or in product quality ensures a higher mark-up per unit, then the greater the number of units sold, the higher will be the value of the future stream of profits. This should hold particularly for process innovation or incremental product innovation, where it is easy to forecast the expected size of the market. On the other hand, introducing either new products or radical product improvements, and forecasting their pace of adoption, are difficult tasks due to the intrinsic uncertainties associated with novelty. According to this view, demand can trigger innovation by reducing uncertainty (i.e. by providing useful knowledge about market need). By reducing firms' uncertainty about expected profits, knowledge can help firms to innovate. Empirically distinguishing between the two effects is difficult for two main reasons. First, it could be argued that it is difficult to establish a clear-cut distinction between the two effects. Both effects might be at work at the same time and might be difficult to disentangle. Second, it should be acknowledged that these effects impinge upon firms' choices in different ways and any empirical tests should take this into account. This paper has attempted to provide some empirical evidence on the impact of these two effects on the likelihood to innovate.

Considering the size of the market as a proxy for the presence of demand, we found support for the idea that the presence of economic incentives stimulates innovation. This is particularly true for process innovation, especially when it is contrasted with product innovation. Considering interaction with customers as a way to reduce uncertainty, we found that firms that considered customers to be the most important contributors for either innovation idea or innovation completion were more likely to consider product innovation as their most economically important innovation.

These results are encouraging, although further corroboration is required. One aspect that should be developed further is the distinction between radical and incremental innovation, on which the issue of uncertainty impinges. Indeed, one of the reasons for the lack of significant positive statistical correlation between uncertainty reduction and product innovation might be that the firms in our sample mainly engage in incremental innovation, in which uncertainty plays a minor role. Investigating this further will be a topic for future research.

Bibliography

- Adner, R. and Levinthal, D. 2001. Demand heterogeneity and technology evolution: Implications for product and process innovation, *Management Science*, vol. 47, no. 5, 611–28
- Berger, A. J. 1975. 'Factors Influencing the Locus of Innovation Activity Leading to Scientific Instrument and Plastics Innovation', SM thesis, Cambridge, MA, Sloan School of Management, MIT
- Boyden, J. W. 1976. 'A Study of the Innovative Process in the Plastics Additives Industry', SM thesis, Cambridge, MA, Sloan School of Management, MIT
- Brouwer, E. and Kleinknecht, A. 1996. Firm size, small business presence and sales of innovative products: a micro-econometric analysis, *Small Business Economics*, vol. 8, 189–201
- Caloghirou, Y., Constantelou, A., and Vonortas, N. S. (eds), 2006. Knowledge Flows in European Industry: Mechanisms and Policy Implications, London, Routledge
- Clark, K. 1985. The interaction of design hierarchies and market concepts in technological evolution, *Research Policy*, vol. 14, 235–51
- Cohen, W. M. and Klepper, S. 1992. The trade off between firm size and diversity in the pursuit of technological progress, *Small Business Economics*, vol. 4, 1–14
- Cohen, W. M. and Klepper, S. 1996A. A reprise of size and R&D, *Economic Journal*, vol. 106, 925–51
- Cohen, W. M. and Klepper, S. 1996B. Firm size and the nature of innovation within industries: the case of process and product R&D, *The Review of Economics and Statistics*, vol. 78, no. 2, 232–43
- Cohen, W. M. and Levinthal, D. A. 1990. Absorptive capacity: a new perspective of learning and innovation, *Administrative Science Quarterly*, vol. 35, 128–52
- Cohen, W. M., Nelson, R. R. and Walsh, J. P. 2002. Links and impacts: The influence of public research on industrial R&D, *Management Science*, vol. 48, no. 1, 1–23
- Czarnitzki, D. and Kraft, K. 2004. Firm leadership and innovative performance: evidence from seven EU countries, *Small Business Economics*, vol. 22, 325–32
- Dosi, G. 1982. Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change, *Research Policy*, vol. 11, no. 3, 147–62
- Dubin, J. A. and Rivers, D. 1989. Selection in linear regressions, logit and probit models, Sociological Methods and Research, vol. 2–3, 360–90
- Freeman, C. 1968. Chemical process plant: innovation and the world market, *National Institute Economic Review*, vol. 45, 29–57
- Freeman, C. and Soete, L. 1997. in *The Economics of Industrial Innovation*, (3rd edn), London, Pinter
- Greene, W. H. 2003. Econometric Analysis, Englewood Cliffs, Prentice Hall
- Heckman, J. J. 1979. Sample selection bias as a specification error, Econometrica, vol. 47, 153-62
- Herstatt, C. and von Hippel, E. 1992. From experience: developing new product concepts via the lead user method: a case study in low tech field, *Journal of Product Innovation Management*, vol. 9, 23–221
- Isenson, R. S. 1969. Project hindsight: an empirical study of the sources of ideas utilized in operational weapon systems, in Gruber, W. H. and Marquis, G. (eds), *Factors in the Transfer of Technology*, Cambridge, MA, MIT Press
- Kleinknecht, A. and Verspagen, B. 1990. Demand and innovation: Schmookler re-examined, *Research Policy*, vol. 19, no. 4, 387–94
- Klepper, S. 1996. Entry, exit, growth, and innovation over the product life cycle, *American Economic Review*, vol. 86, no. 3, 562–83
- Klepper, S. and Thompson, P. 2007. Submarkets and the evolution of market structure, *Rand Journal of Economics*, vol. 34, no. 4, 862–88
- Kremer, M., Glennester, R. and Williams, H. 2006. Creating markets for vaccines, *Innovations*, vol. 1, no. 1, 67–79
- Langrish, J., Gibbons, M., Evans, W. G. and Jevons, F. R. 1972. Wealth from Knowledge: A Study of Innovation in Industry, New York, John Wiley
- Laursen, K. and Salter, A. 2006. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms, *Strategic Management Journal*, vol. 27, no. 2, 131–50

- Levin, R., Klevorick, A., Nelson, R. R. and Winter, S. G. 1987. Appropriating the returns from industrial R&D, Brookings Papers on Economic Activity, 820
- Lichtenberg, F. and Waldfogel, J. 2003. , 'Does Misery Love Company? Evidence from Pharmaceutical Markets Before and After the Orphan Drug Act', NBER Working Paper No. 9750
- Link, A. N. 1982. A disaggregated analysis of industrial R&D: product versus process innovation, in Sahal, D. (ed.), *The Transfer and Utilization of Technical Knowledge*, Lexington, MA, Lexington Books
- Lionetta, W. 1977. 'Sources of Innovation Within the Pultrusion Industry', unpublished SM thesis, Sloan School of Management, Cambridge, MA, MIT
- Malerba, F. 2002. Sectoral systems of innovation and production, *Research Policy*, vol. 31, 247-64
- Malerba, F., Nelson, R. R., Orsenigo, L. and Winter, S. G. 2007. Demand, innovation and the dynamics of market structure: the role of experimental users and diverse preferences, *Journal of Evolutionary Economics*, vol. 17, no. 4, 371–99
- Mohen, P. and Hoareau, C. 2003. What type of enterprises forges close links with universities and government labs? Evidence from CIS 2, *Managerial and Decision Economics*, vol. 24, 133–45
- Morrison, P. D., Roberts, J. H. and von Hippel, E. 2000. Determinants of user innovation and innovation sharing in a local market, *Management Science*, vol. 46, no. 12, 1513–27
- Mowery, D. C. and Rosenberg, N. 1979. The influence of market demand upon innovation: a critical review of some recent empirical studies, *Research Policy*, vol. 8, 102–53
- Myers, S. and Marquis, D. G. 1969. in *Successful Industrial Innovation*, Washington, National Science Foundation

National Science FoundationReport on Project TRACES, Washington

- Pavitt, K. 1984. Patterns of technical change: towards a taxonomy and a theory, *Research Policy*, vol. 11, no. 1, 33–51
- Pavitt, K., Robson, M. and Towsend, J. 1987. The size distribution of innovating firms in the UK: 1945–1983, *Journal of Industrial Economics*, vol. 35, 291–316
- Popp, D. 2002. Induced innovation and energy prices, *American Economic Review*, vol. 92, 160–80
- Reinganum, J. 1989. The timing of innovation: research, development and diffusion, in Schmalensee, R. and Willig, R. (eds), *Handbook of Industrial Organization, Vol. I, Amsterdam, North-Holland*
- Rothwell, R. and Freeman, C. 1974. SAPPHO Updated Project SAPPHO Phase II, *Research Policy*, vol. 3, 258–91
- Sakakibara, M. and Porter, M. E. 2001. Competing at home to win abroad: evidence from Japanese industry, *Review of Economics and Statistics*, vol. 2, 310–22
- Scherer, F. 1982. Demand pull and technological invention: Schmookler revisited, *Journal of Industrial Economics*, vol. 30, 225–37
- Scherer, F. 1991. Changing perspectives on the firms size problem, in Acs, Z. J. and Audretsch, D. B. (eds), *Innovation and Technological Change. An International Comparison*, New York, Harvester Wheatsheaf
- Schmookler, J. 1962. Economic sources of inventive activity, Journal of Economic History, vol. 22, no. 1, 1–20
- Schmookler, J. 1966. in Invention and Economic Growth, Cambridge, MA, Harvard University Press
- Sutton, J. 1998. in Technology and Market Structure: Theory and History, Cambridge, MA, MIT Press
- Teubal, M. 1979. On user needs and need determination: aspects of the theory of technological innovation, in Baker, M. (ed.), *Industrial Innovation: Technology, Policy, Diffusion*, London, MacMillan
- van de Ven, W. and van Praag, B. 1981. The demand for deductibles in private health insurance: a probit model with sample selection, *Journal of Econometrics*, vol. 22, 229–52
- von Hippel, E. 1978. Successful industrial products from customer ideas, *Journal of Marketing*, vol. 42, no. 1, 39–49
- von Hippel, E. 1982. Appropriability of innovation benefit as a predictor of the source of innovation, *Research Policy*, vol. 11, 95–115

von Hippel, E. 1986. Lead users: a source of novel product concepts, *Management Science*, vol. 32, 791–805

von Tunzelmann, N. and Wang, Q. 2003. An evolutionary view of dynamic capabilities, *Economie Appliquee*, vol. LVI, no. 3, 33-64

Appendix

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Table	A1.	Correlation	matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1														
2	0.041	1													
3	-0.092	-0.068	1												
4	0.034	0.135	-0.085	1											
5	-0.048	0.019	-0.072	-0.018	1										
6	-0.070	-0.017	0.071	0.006	-0.068	1									
7	0.231	0.024	-0.123	-0.024	0.005	-0.065	1								
8	-0.137	0.134	0.086	-0.035	0.077	0.072	-0.060	1							
9	0.058	0.123	0.051	-0.021	0.071	0.061	-0.034	0.051	1						
10	0.024	-0.117	0.073	-0.050	0.274	0.087	0.033	-0.044	0.044	1					
11	0.034	-0.055	-0.051	0.044	-0.111	-0.020	-0.010	-0.078	0.007	0.008	3 1				
12	2 0.034	-0.021	-0.003	-0.068	-0.113	0.109	0.033	-0.038	0.103	-0.116	5 -0.310	1			
13	3 -0.022	0.027	0.101	-0.023	-0.183	-0.045	-0.049	0.052	-0.072	0.094	4-0.262	-0.262	2		
14	4-0.087	0.032	-0.000	0.088	-0.128	-0.036	0.038	0.050	0.034	-0.086	6-0.171	-0.171	-0.144	1	
15	5 0.009	0.029	-0.036	-0.011	0.453	-0.025	-0.005	0.034	-0.065	0.075	5 -0.330	-0.330	0-0.279	-0.182	1

1, Selection; 2, NEW PROC & NEW PROD; 3, Most important innovation; 4, EXT INTER; 5, MKT SIZE; 6, NO OF COMPETITORS; 7, CUST INTER; 8, EMP; 9, R&D; 10, HEADQ; 11, Food and beverages; 12, Chemicals; 13. Communcations equipment; 14, Telecommunication services; 15, Computer services.