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INNOVATION AND WELFARE:
RESULTS FROM JOINT ESTIMATION OF PRODUCTION AND DEMAND FUNCTIONS

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ABSTRACT

This paper develops a simple framework to estimate the parameters of the production function together with the elasticity of the demand for the output and the impact of demand and cost shifters. The use of this framework helps, in the first place, to treat successfully the difficult problem of the endogeneity of input quantities. But it also provides a natural way to assess the welfare effects of firms' innovative actions by estimating their impact on both cost and demand. We show that the total current period (static) welfare gains of introducing a process or a product innovation are, on average, about 1.6% and 4%, respectively, of the value of the firm's current sales. The increase in consumer surplus amounts to two- thirds of these gains in the first case and half in the second.

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1.Introduction

This paper develops a simple framework to estimate the parameters of the production function together with the elasticity of the demand for the output and the impact of demand and cost shifters.The estimation of cost and demand parameters together with the production function serves two purposes. Firstly, it helps to deal succesfully with one of the most difficult problems in estimating production functions, the endogeneity of the input quantities. Secondly, it provides a natural framework to assess the effects of firms' innovative actions by estimating their impact on both cost and demand. The framework needs information on prices, innovation data, and other demand shifters, but it nicely illustrates how much can be gained by having this information. We show that the total current period (static) welfare gains of introducing a process or a product innovation are, on average, about 1.6% and 4%, respectively, of the value of the firm's current sales. Increase of consumer surplus amounts to two-thirds of the effect in the first case and half in the second.

Estimation of microeconomic production functions has proved to be a hard task because of the simultaneous determination of output and relevant inputs by the same partially unobserved forces. Both chosen input quantities and produced ouput are partially determined by the unobservable productivity level which characterises the firm-specific production function and that is likely to evolve over time endogenously and in complex ways.[1] Firms engage in R&D expenditures and introduce process and product innovations with the aim of enhancing productivity, and the results are partly random because these activities and their results are subject to uncertainty. The problem of simultaneous determination of inputs and output, as well as the relevance of the simultaneous equations framework for dealing with this setting, was first stressed by Marschak and Andrews (1944). Griliches and Mairesse (1998), and more recently, Ackerberg, Benkard, Berry and Pakes (2005), have surveyed the efforts to develop estimation methods which are robust to the simultaneity biases.

Two methods have dominated the most recent approaches. One stresses the equation

[1] This unobservability may also eventually create a selectivity problem because firms with the worst productivity performance may be induced to leave the market.

transformations under which the unobserved productivity levels of the production relationship are likely to be differenced out, or at least reduced to limited forms of residual correlation. Then it proposes the use of suitable lags of the variables as instruments (IV) orthogonal to the remaining disturbances to obtain identification. Panel “fixed effects” assumptions about productivity and the estimation of equations in first differences belong to this tradition. Blundell and Bond (2000), for example, present a sophisticated variety of this strategy which allows for an unobserved composite term consisting of a "fixed effect," an autoregresive component and an uncorrelated disturbance, and derive the right moments to be employed in this context. [2]

The alternative approach proposes semiparametric methods to control for (Markovian) correlated productivity terms, based on the observability of the investment (or, more in general, input choice) decisions of the firms. Optimal input decisions convey information about the level of productivity, and if the corresponding demands can be inverted, they can be used to replace the unobserved term. With unobserved productivity adequately controlled for, correlation of input quantities ceases to be a problem. Olley and Pakes (1996) first proposed this method, which has also been developed by Levinsohn and Petrin (2002) and Ackerberg, Caves and Frazer (2007) and applied by many others. Doraszelski and Jaumandreu (2007) extend the method to consider unobserved productivity which evolves under the influence of R&D investments, i.e., endogenously.

Against this background, this paper aims to explore the use of information on the firm-level prices and shifters to identify the parameters of the production function. It takes seriously the often quoted reference of Griliches that addressing the simultaneity problem is harder “without constructing a complete production and input decision behavior model.” We draw on the idea first discussed in Griliches and Mairesse (1984) about how to deal with the simulaneity-induced problems by using semi-reduced forms of the relevant eco-

[2] Given the difficulties with this type of estimator, they argue that standard panel first-difference GMM estimates are likely to present large finite-sample biases due to the time series persistence properties of some of the variables involved. They propose exploiting additional instruments in an extended GMM estimator which includes level moments.

nomic system. The framework is very simple: by specifying the system of equations which determines output and (variable) inputs, one includes enough exogenous variables to solve and express every endogenous variable in terms of its exogenous determinants. Then a straightforward LS estimator can be applied with much weaker assumptions about the evolution of the unobservables, and the structural parameters can be recovered by one of the usual methods.

Following Griliches and Mairesse (1984), we enlarge the model by considering that firms compete in an imperfectly competitive environment, experiencing a downward-sloping demand for their products, and that price must therefore be taken as an additional endogenous variable simultaneously set by the firm.[3] Hence we consider that the suitable system of equations includes the production function, the (dual) cost function and the derived input demand relationships, the demand for the firm product and the pricing rule. In this setting, we show that both the production function and the cost equation can be rewritten in terms of exogenous determinants in addition to the fixed factors (semi-reduced form) and used to estimate the relevant parameters. We should remark, however, that we will find some need for partly instrumenting the input prices as we use observed prices that are only rough measures of the relevant shadow prices.[4] We also derive an alternative semi-reduced form consisting of the equation for output and specifying the other as an equation for price. This specification adds a little complexity as the new equation must explain possible changes in margins in addition to costs.

We hence enlarge the system employed in Griliches and Mairesse (1984) by adding a firm-specific demand relationship, which we specify depending on unobserved demand ad-

[3] If firms were perfectly competitive, the production function (with short-run decreasing returns to scale) combined with equations of demand for variable inputs, depending on output quantity and output and input prices, would be all that is needed to obtain a set of semi-reduced form equations. When firms must be taken as having some market power, price becomes an endogenous variable set with a markup on marginal cost (which through duality inherits all unobserved efficiency that production function may have) according to the state of competition.

[4] Shadow prices are the consequence of input adjustment costs. For recents discussions on these costs, see, for example, Delgado, Jaumandreu and Martin-Marcos (1999) and Bond and Soderbom (2005).

vantages and observed demand shifters and price, as well as a firm pricing rule. Imperfect competition therefore gives rise to a more complex system, but also gives a natural and theoretically sound role for the use of demand shifters in the identification of the production function. In addition, the method has the important advantage that it does not rely on specific distributional assumptions about productivity and other unobservables. The main requirement is, however, firm-specific information good enough to estimate the resulting system.

Demand is, however, much more than a device to help to estimate the parameters of the production function consistently. It adds the piece which is just needed to assess the welfare effects of the innovative actions of the firms. The production function and its dual, the cost function, estimate at most the cost effects of innovation. Process innovation, aimed at reducing production costs, will show that its effect is to increase productivity and reduce costs. Product innovation, aimed at enlarging demand, will not show any effect if it has no cost or a small amount of cost consequences. The demand relationship adds the possibility of asssessing the impact of product innovation and, more generally, the profitability of any type of innovation and its associated consumer surplus effects. The profitability of a cost-reducing innovation is only measurable if one can estimate how it is translated into a demand enlargement. The profitability of a product innovation is to be assessed just by the amount of this enlargement, and demand is the instrument needed to assess the increases in consumer surplus associated with both demand enlargements.

By adding the estimation of demand parameters, we hence add the possibility of computing the private and social returns of innovation.[5] In addition, this renders it possible to compare them to their observed costs in the form of R&D expenditures. This has a potential of applications that we plan to illustrate. Firstly, by comparing profits and costs, one can derive the degree of current incentives, the anatomy of costs, especially the presence and size of sunk costs, and the likely presence and size of "market failures" (socially profitable innovations subject to zero or negative private profitabilities). Secondly, by measuring how

[5] Measuring welfare gains from innovation, particularly product innovation, is a hot topic which begins with Trajtemberg (1993) and Hausman (1997).

firms discount static profits over time, one can learn about the uncertainties of innovation expenditures and the intensity of competition. We want to address some of these points in future versions of this paper, in which we also plan to allow for more heterogeneous firm demands.

Using a rich data set consisting of (unbalanced) observations on almost 1,000 Spanish manufacturing firms during the period 1990-1999, we present production function parameter estimates along an estimate for the elasticity of demand and the impact of cost and demand shifters. We apply the estimator to relatively small samples for 6 industries, which allows us to take into account the heterogeneity in production as well as check the feasibility and robustness of our estimator. Information on firms includes firm-level variations for the price of the output and the price of the inputs, the introduction of technological (process and product) innovations and additional demand shifters. We estimate the structural parameters from the semi-reduced forms using non-linear GMM methods, but we report and discuss in appendices some estimates obtained with conventional OLS and IV estimators.

The rest of the paper is organised as follows. Section 2 explains the theoretical framework and derives the semi-reduced forms. Section 3 explains the data and presents the econometric specification and method of estimation. Section 4 presents the main estimates and Section 5 concludes. One data appendix provides some detail on the sample, the employed variables and descriptive statistics and another gives information on some previous estimates.

2. A semi-reduced form system

2.1 Production and demand

Assume that firms have production functions of the form $Q = F(Z_1, \overline{X}, X)\exp(\omega_1)$, where Q represents output, Z_1 is a vector of productivity (and hence cost) shifters, $\overline{X}$ stands for a vector of fixed inputs, X for variable inputs and $\exp(\omega_1)$ represents the firm-idiosycratic productivity level reached by the firm (we drop firm and time subindices for simplicity and we adopt a quite common notation to express productivity). Assume at the same time that the production function is (perhaps locally) homogeneous to degree μ in the variable inputs; i.e., μ is the sum of the elasticities of these inputs. The terms $\exp(\omega_1)$ are observed by the firm, but not for the econometrician, and evolve over time in an unspecified manner. The most usually considered productivity shifter is process innovation. Note that the production function assumptions imply a dual cost function of the form $C = C^*(Z_1, W, \overline{X})(Q/\exp(\omega_1))^{1/\mu}$, where W stands for the vector on variable input prices. Firms are going to choose Q and X simultaneously and we assume, without loss of generality, that firms choose X in order to minimize costs given $\exp(\omega_1)$.In what follows, we explain how firms determine Q.

Assume that there is some product differentiation among the firms which compete in a given market. Demand for a firm's product is given by a firm-specific demand function of the form $Q = Q(Z_2, P)\exp(\omega_2)$, where Z_2 is a vector of demand shifters and P is the price set by the firm. Idiosyncratic demand terms $\exp(\omega_2)$ reflect persistent demand advantages and firm-specific demand shocks, both observed only by the firm. To simplify notation, we assume the prices of rivals included among the shifters.[6] Other demand shifters may be either exogenously driven (e.g., the state of the market) or reflect firm investments (e.g., advertising and product innovation).

The elasticity of demand with respect to P must be understood as the structural elasticity, which mainly reflects the degree of product differentiation. In fully competitive situations, it may tend to (minus) infinity. We assume P is the result of firms pricing according to the rule $P = (1+m)C'$, where C' stands for (short-run) marginal cost and m is the markup which results from the particular behavior of firms. Notice that we keep ourselves impartial to the particular games that firms play by specifying a general markup m which may be consistent with different equilibria. We will only care about possible changes of m over time, not about their level.

Assume that firms set prices given the state of demand and then variable input quantities are chosen (at competitive prices, but possibly subject to adjustment costs) according to the

[6] In practice, rivals' prices are not observable and we will assume that their effect is picked up by the time dummies.

output to be produced and the level reached by productivity. Input quantities are therefore endogenous in the production function relationship (i.e., they are correlated with the unobserved term $\exp(\omega_1)$). However, consideration of the way the firm sets price according to demand, and hence also decides output, brings in a natural set of structural exogenous or predetermined determinants for output and inputs. They can be used, together with input prices and other cost shifters, to write reduced form equations for output and cost. This is shown in what follows.

We are going to set our model in terms of growth rates, log-differencing the involved equations. This has at least two advantages. Firstly, we can then use in the analysis some variables which are available only in terms of growth (e.g., price growth rates, which correspond to price indices whose levels are meaningless). Secondly, we can deal more safely with a high degree of heterogeneity. Unobservable firm-specific, time-invariant effects are differenced out; we do not need to specify markup levels, and equations in terms of growth rates may be thought of as approximating general functional forms. On the other hand, our exercise supports the idea that a suitable econometric specification in first differences plus high quality data produce satisfactory results [7]

2.2 Differencing the equations

Assuming that there are R and J fixed and variable factors respectively, log-differencing the production function gives[8]

[7] An important problem has been attributed to the employment of differences in the context of highly persistent data (see, for example, Blundell and Bond, 2000) : the lack of correlation between current growth rates and past levels of the variables may seriously bias IV estimators. But this lack of correlation can be seen just as a third advantage in our context. As we are going to use only rates of change of exogenous and predetermined variables as regressors, we can expect no correlation between regressors and errors, even with serially correlated residuals.

[8] A disturbance term, uncorrelated with the included variables, can be added meaningfully to each of the relationships that we discuss in what follows without any substantial change in the results. We avoid doing this only for simplicity of notation.

$$q = z_1 + \sum_r \varepsilon_r \overline{x}_r + \sum_j \varepsilon_j x_j + \Delta\omega_1 \tag{1}$$

where small letters stand for growth rates. Writing c for the rate of growth of average variable-cost ($c = \frac{d(C/Q)}{C/Q}$), we can obtain the log-differenced average cost function which follows

$$c = -z_1 - \frac{1}{\mu}\sum_r \varepsilon_r \overline{x}_r + \frac{1}{\mu}\sum_j \varepsilon_j w_j + (\frac{1}{\mu} - 1)q - \frac{\Delta\omega_1}{\mu} \tag{2}$$

First-order conditions of cost minimisation for each variable input are given by $C' \frac{\partial F}{\partial x_j} = w_j$, which can be manipulated to obtain the cost-share/input-elasticities equality $\frac{w_j x_j}{(C/Q)Q} = \frac{\varepsilon_j}{\mu}$, which give the relationships

$$x_j = q - (w_j - c) \tag{3}$$

Endogeneity of x_j in equation [1] must be understood as the effect of its determination through the q and c values, which contain ω_1.

Log-differentiation of demand gives the relationship

$$q = z_2 - \eta p + \Delta\omega_2 \tag{4}$$

where η stands for the elasticity of demand with respect to the product price. And, at the same time, the log differences of the pricing rule can be written as

$$p = \Delta m + c \tag{5}$$

where Δm stands for the markup changes.

Let us briefly discuss the nature of the terms $\Delta\omega_1$ and $\Delta\omega_2$ before using these equations. Even if ω_1 and ω_2 are time persistent, their differences can range from serially uncorrelated disturbances to fully autocorrelated errors depending on the specific assumptions one is willing to make.[9] Fortunately, we are not obliged to make a choice. We simply assume that

[9] According to the current assumptions in the specification of production functions, the term $\Delta\omega_1$ can be:

$\Delta\omega_1 \equiv u_1$ is a distributionally unspecified disturbance potentially correlated with current and possibly past input choices and that the same goes for $\Delta\omega_2 \equiv u_2$.

2.3 Reduced form

Now we are ready to use the system of equations (1)-(5) to obtain reduced forms for q and c, respectively. Using (5) and (4) to express c in terms of q, the demand shifters and margin changes. Then, replace the c which appears in [2] with this expression. Input changes can be written as $x_j = (1 - \frac{1}{\eta})\ q - w_j + \frac{z_2}{\eta} - \Delta m + \frac{u_2}{\eta}$. It follows that

$$q = \beta_1 z_1 + \sum_r \beta_r \overline{x}_r - \sum_j \beta_j w_j + \beta_2 z_2 - \beta_m \Delta m + v_1 \tag{6}$$

where $\beta_1 = \frac{1}{d}$, $\beta_r = \frac{\varepsilon_r}{d}$, $\beta_j = \frac{\varepsilon_j}{d}$, $\beta_2 = \frac{\mu}{\eta d}$, $\beta_m = \frac{\mu}{d}$, $d = 1 - (1 - \frac{1}{\eta})\mu$, and $v_1 = \frac{1}{d}u_1 + \frac{\mu}{\eta d}u_2$.

Similarly, p can be replaced in (4) using equation (5). Then we have output changes in terms of demand shifters, margin changes and c; that is, $q = z_2 - \eta\Delta m - \eta c + u_2$. Substituting this for q in equation (3), we obtain

$$c = -\delta_1 z_1 - \sum_r \delta_r \overline{x}_r + \sum_j \delta_j w_j + \delta_2 z_2 - \delta_m \Delta m + v_2 \tag{7}$$

where $\delta_1 = \frac{1}{\eta d}$, $\delta_r = \frac{\varepsilon_r}{\eta d}$, $\delta_j = \frac{\varepsilon_j}{\eta d}$, $\delta_2 = \frac{1-\mu}{\eta d}$, $\delta_m = \frac{1-\mu}{d}$ and $v_2 = -\frac{1}{\eta d}u_1 + \frac{1-\mu}{\eta d}u_2$.

To implement the system, the effects represented by z_1, z_2 and Δm must of course be measured by specific indicators. But, in principle, all explanatory variables in equations (6) and (7) can be considered, under appropriate assumptions, to be either exogenous (w, at least when observed prices are enough, and shifters exogenous) or predetermined ($\overline{x}$ and

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a) a serially uncorrelated disturbance, because ω_1 is a random walk (i.e., $\omega_{1t} = \omega_{1t-1} + \epsilon_{1t}$ with $\epsilon_{1t} \sim MA(0)$, an uncorrelated residual); b) a disturbance presenting a limited serial correlation, because ω_1 has two components, a "fixed" component which remains unchanged over time and a time- varying uncorrelated shock (e.g., $\omega_{1t} = \omega_1 + \epsilon_{1t}$ with $\epsilon_{1t} \sim MA(0)$ and hence $\Delta\omega_{1t} = (\epsilon_{1t} - \epsilon_{1t-1}) \sim MA(1)$); c) a serially correlated disturbance because ω_1 follows an $AR(1)$ (i.e., $\omega_{1t} = \rho\omega_{1t-1} + \epsilon_{1t}$ and hence $\omega_{1t} - \omega_{1t-1} = -(1-\rho)\omega_{t-1} + \epsilon_{1t}$) or a combination of this and an $MA(0)$ disturbance; see, e.g., Blundell and Bond (2000); d) a serially correlated disturbance because ω_1 follows an unspecified Markov process (i.e., $\omega_{1t} = g(\omega_{1t-1}) + \epsilon_{1t}$ and hence $\omega_{1t} - \omega_{1t-1} = g(\omega_{t-1}) - g(\omega_{t-2}) + \epsilon_{1t} - \epsilon_{1t-2}$); see, e.g., Olley and Pakes (1996).

perhaps some endogenous shifters). Disturbances u_1 and u_2 are presumably correlated, and their structure depends on the properties of $\omega_1$and ω_2. The relationships involved allow for the identification of the production function and demand parameters.[10] The structure of the elasticities is identified in each equation, but total short and long-run elasticities can only be identified using both equations to obtain η.

Alternatively, the second equation can be set in terms of price. Using (4) to replace q in (2) and plugging the result in (5) gives the following equation

$$p = -\gamma_1 z_1 - \sum_r \gamma_r \overline{x}_r + \sum_j \gamma_j w_j + \gamma_2 z_2 + \gamma_m \Delta m + v_2' \tag{8}$$

where $\gamma_1 = \frac{1}{\eta d}$, $\gamma_r = \frac{\varepsilon_r}{\eta d}$, $\gamma_j = \frac{\varepsilon_j}{\eta d}$, $\gamma_2 = \frac{1-\mu}{\eta d}$, $\gamma_m = \frac{\mu}{\eta d}$ and $v_2' = \frac{1-\mu}{\eta d} u_2$.

The system in terms of price may in principle separately identify the effects of one particular variable if this variable is having an effect as a demand shifter and another as a markup shifter. For this reason, and in particular for testing the presence of such effects, this equation may play a useful role (see below).

2.4 Testing

The previous framework allows for testing the specification of the effects quite easily. Suppose firstly that there is a demand shifter that is also a potential shifter of productivity (or vice-versa). For example, let's say that we want to know if product innovations have a productivity effect (i.e., they should be included in the production function in addition to their role as a shifter of the demand function). Let the corresponding indicator be called z and let the effects be specified as $z_1 = \varepsilon_z^{PF} z$ and $z_2 = \varepsilon_z^{D} z$. If $\varepsilon_z^{PF} \neq 0$ and $\varepsilon_z^{D} \neq 0$, in the

[10] Parameters of the two equations are subject to the following relationships: $\eta = \frac{\beta_1}{\delta_1} = \frac{\beta_r}{\delta_r} = \frac{\beta_j}{\delta_j}$, $\frac{\beta_2}{\delta_2} = \frac{\mu}{1-\mu}\eta$, $\frac{\beta_m}{\delta_m} = \frac{\mu}{1-\mu}$ and $\mu = \frac{\eta \sum \beta_j}{\eta + (\eta-1)\sum \beta_j}$, $\varepsilon_j = \frac{\eta \beta_j}{\eta + (\eta-1)\sum \beta_j}$, $\varepsilon_r = \frac{\eta \beta r}{\eta + (\eta-1)\sum \beta_j}$ or, in terms of the δ parameters, $\mu = \frac{\eta \sum \delta_j}{1 + (\eta-1)\sum \delta_j}$, $\varepsilon_j = \frac{\eta \delta_j}{1 + (\eta-1)\sum \delta_j}$ and $\varepsilon_r = \frac{\eta \delta r}{1 + (\eta-1)\sum \delta_j}$. Long run elasticity of scale is $\sum \varepsilon_r + \sum \varepsilon_j$.

output and cost equations we have total effects

$$\begin{aligned}
\frac{1}{d}\varepsilon_z^{PF} z + \frac{\mu}{\eta d}\varepsilon_z^{D} z &= \frac{\mu}{\eta d}(\frac{\eta}{\mu}\varepsilon_z^{PF} + \varepsilon_z^{D})z \\
-\frac{1}{\eta d}\varepsilon_z^{PF} z + \frac{1-\mu}{\eta d}\varepsilon_z^{D} z &= \frac{1-\mu}{\eta d}(-\frac{1}{1-\mu}\varepsilon_z^{PF} + \varepsilon_z^{D})z
\end{aligned}$$

and $H_0 : \varepsilon_z^{PF} = 0$ can be tested simply as the equality of the elasticity coefficients on variable z in both equations.

Suppose now that we have doubts about the possible effect of variable z on the markup (suppose, for example, that the question is whether product innovation changes margins in addition to shifting demand). Specify the effects as $z_2 = \varepsilon_z^D z$ and $\Delta m = \varepsilon_z^M z$. If $\varepsilon_z^D \neq 0$ and $\varepsilon_z^M \neq 0$, in the output and price equations we have total effects

$$\begin{aligned}
\frac{\mu}{\eta d}\varepsilon_z^{D} z - \frac{\mu}{d}\varepsilon_z^{M} z &= \frac{\mu}{\eta d}(\varepsilon_z^{D} - \eta\varepsilon_z^{M})z \\
\frac{1-\mu}{\eta d}\varepsilon_z^{D} z + \frac{\mu}{d}\varepsilon_z^{M} z &= \frac{1-\mu}{\eta d}(\varepsilon_z^{D} - \frac{\mu}{1-\mu}\varepsilon_z^{M})z
\end{aligned}$$

and $H_0 : \varepsilon_z^M = 0$ can be tested simply as the equality of the elasticity coefficients on variable z in both equations. It is easy to check that, in this case, the test cannot be performed in the ouput and cost equations (both elasticities are equal, conveying the same mix of the two effects).

3. Data and econometric specification

3.1 Data

We present estimates based on six (unbalanced) industry samples, which amount to a total of nearly 1,000 Spanish manufacturing firms, observed during the period 1990-1999. All variables come from the survey ESEE (Encuesta Sobre Estrategias Empresariales), a firm-level panel survey of Spanish manufacturing starting in 1990. At the beginning of this survey, firms with fewer than 200 workers were sampled randomly by industry and size strata, retaining 5%, while firms with more than 200 workers were all requested to participate, and the positive answers represented more or less a self-selected 60%. To preserve representation, samples of newly created firms were added to the initial sample every subsequent year. At the same time, there are exits from the sample, coming from both death and attrition. The survey then provides a random sample of Spanish manufacturing with the largest firms oversampled. A Data Appendix provides details on the variables definition, sample composition, industry breakdown and reports some descriptive statistics.

Information on the firms include, in addition to the usual output and input quantity measures, the firm-level variations for the price of the output and the price of the inputs, the introduction of technological (process and product) innovations, and some demand shifters. Let us detail the variables. Firstly, we have the more usual variables: output (deflated production), an estimate of capital stock, labor measured in total (effective) hours of work, intermediate consumption (also deflated) and the firm's self reported utilisation of the standard capacity of production. In addition, we compute variable cost as the sum of the wage bill and intermediate consumption, and estimate the hourly wage by dividing the wage bill by total hours of work. But we also have some less usual firm-level variables which play a key role in our estimations. Firstly, we have the yearly (average) output price change as reported by the firm. Secondly, firms also provide an (average) estimate of the change in the cost of inputs grouped in three sets: energy, materials and services, which are combined in a price index for materials. Finally, we can compute a firm specific user cost of capital using the interest rate paid by the long-term debt of the firm plus the rough estimate of a 0.15 depreciation rate and minus the consumer prices index variation. In addition, we are going to use the following shifters: a dummy representing the introduction of process innovations, a dummy reporting the introduction of product innovations, the rate of increase of firm advertising, and an index of the dynamism of the firm's specific market. As we have no observations on rivals' prices , we will let the time dummies pick up their effect.

From the start, we are going to assume some constraints on the specification of the shifters. We take the introduction of process innovations as a cost (and only cost) shifter. At the same time, we will assume that there are three demand shifters: product innovations, advertising and market dynamism. Let us suppose for the moment that there are no margin changes, although it seems pretty clear that all these demand shifters can also induce changes in margins.

3.2 Specification and indentification conditions

Our specification of the reduced form for output (6) will include: the fixed input capital k, the prices of variable inputs (wage, w, and materials, p_M), and the shifters. Let us denote i for the introduction of innovations (with pc for process and pd for product), d for market dynamism and a for the growth rate of advertising. After some experimenting, we decided to enter utilisation of capacity uc restraint to have the same coefficient as capital. Our specification for the reduced form for cost (7) will include the same variables, although affected by different theoretically constrained coefficients. A set of time dummies is included in each equation, with no cross restrictions but coefficients constrained to add up to zero in each equation. Hence the system is

$$\begin{aligned} q &= \beta_0 + \beta_{pc} i_{pc} + \beta_k (k + uc) + \beta_w w + \beta_M p_M + \beta_{pd} i_{pd} + \beta_a a + \beta_d d + time + v_1 \\ c &= \delta_0 + \delta_{pc} i_{pc} + \delta_k (k + uc) + \delta_w w + \delta_M p_M + \delta_{pd} i_{pd} + \delta_a a + \delta_d d + time + v_2 \end{aligned}$$

where $\beta_{pc} = \frac{\varepsilon_{pc}}{1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)}$, $\delta_{pc} = -\frac{\varepsilon_{pc}}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$, $\beta_k = \frac{\varepsilon_k}{1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)}$, $\delta_k = -\frac{\varepsilon_k}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$, $\beta_w = -\frac{\varepsilon_l}{1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)}$, $\delta_w = \frac{\varepsilon_l}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$, $\beta_M = -\frac{\varepsilon_M}{1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)}$, $\delta_M = \frac{\varepsilon_M}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$ and $\beta_i = \frac{\mu\varepsilon_i}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$, $\delta_i = \frac{(1-\mu)\varepsilon_i}{\eta\left[1-(1-\frac{1}{\eta})(\varepsilon_l+\varepsilon_M)\right]}$ for $i = pd, a, d$.

So we have a two-equation model with nonlinear cross-restrictions in the parameters which can identify production elasticities, returns to scale and demand elasticity as well as the impact of the shifters. In what follows, let us briefly discuss the identification conditions of the specification.

Firstly, under competitive factor markets and no measurement problems, we can expect the input prices to be orthogonal to both equation errors, i.e., $E(wv) = 0$ and $E(p_M v) = 0$. Secondly, we can assume that the cost and demand shifters are orthogonal to the primitive

u errors of the production function and demand equations, and hence also orthogonal to both equation errors. This doesn't need much discussion for the case of the indicator of market dynamism, which repesents the exogenous market conditions in which the firm is involved. It seems quite sensible also for the dummies representing the introduction of innovations. Even if the introduction of innovations can perhaps be related to past unobserved firm-level productivity (for example, through investment in R&D), it is more difficult to think of reasons why this relation should carry over the contemporaneous change in the level of productivity. And the same can be said for the rate of change in advertising expenditures, although here perhaps it could be argued that some advertising can be aimed at counterbalancing expected adverse demand shocks inducing some correlation. Thirdly, both equations include the predetermined input capital that, with u_1 and u_2 autocorrelated and presumably inducing autocorrelation in v_1 and v_2, cannot be considered exogenous. That is, we expect $E(\overline{x}v) \neq 0$ and some instrument must be used at least for this variable. We are going to use the price condition that presumably determines the level of investment in the long run: the user cost of capital r.

Although dicussion points to the necessity of only one instrument, in practice, preliminary estimates quickly showed that some instrumenting of the input prices was needed to obtain sensible coefficients. The likely reason is the errors that observed prices include with respect to prices relevant to the firm maximization problem. Even setting aside pure measurement problems, the costs of adjustment of the inputs make unobserved "shadow" prices relevant, at least for replacing quantities. This only affects the first equation. We try to solve the need to predict the right "shadow" prices for wages and the price of materials in the first equation by using the effective hours per worker (ehw) and a variable representing market-wide price decreases (mpv, which we assume are correlated to materials price changes). So, our basic instrument sets can be written as $Z_1 = \{1, i_{pc}, i_{pd}, a, d, time, ehw, mpv, r, uc\}$ and $Z_2 = \{1, i_{pc}, i_{pd}, a, d, time, w, p_M, r, uc\}$. In practice, we use two versions of the user cost instrument: the user cost of capital for the firm itself and the user cost of capital for the rivals, computed using data on the rest of the firms in the same industry. We also use the square of both variables as instruments.

3.3 Econometric method

The model fits most naturally in the non-linear two-equation GMM problem

$$\min_{\theta} \begin{bmatrix} \frac{1}{N}\sum_i Z'_{1i}v_{1i} \\ \frac{1}{N}\sum_i Z'_{2i}v_{2i} \end{bmatrix}' A \begin{bmatrix} \frac{1}{N}\sum_i Z'_{1i}v_{1i} \\ \frac{1}{N}\sum_i Z'_{2i}v_{2i} \end{bmatrix}$$

where Z_{ji} is $T_i \times k_j$, with $j = 1, 2$ and $i = 1...N$ and which can be implemented using a first-step weighting matrix

$$A = \begin{bmatrix} (\frac{1}{N}\sum_i Z'_{1i}Z_{1i})^{-1} & 0 \\ 0 & (\frac{1}{N}\sum_i Z'_{2i}Z_{2i})^{-1} \end{bmatrix}$$

A robust variance estimate of the parameters can then be obtained by employing the formula $Var(\theta) = (\Gamma' A\Gamma)^{-1}\Gamma' AE(Z'_i v_i v'_i Z_i)A\Gamma(\Gamma' A\Gamma)^{-1}$, where $\Gamma = E(\frac{\partial(Z'_i v_i)}{\partial\theta})$ is estimable using $\frac{1}{N}\sum_i \frac{\partial(Z'_i\widehat{v}_i)}{\partial\theta}$ and $E(Z'_i v_i v'_i Z_i)$ by using $\frac{1}{N}\sum_i Z'_i\widehat{v}_i\widehat{v}'_i Z_i$.In practice, the equations can be "concetrated out" for the estimation of parameters which enter linearly and the non-linear search is only over $\varepsilon_k, \varepsilon_l, \varepsilon_M, \eta$ and $\varepsilon_{pc}, \varepsilon_{pd}, \varepsilon_a$ and ε_d.

4. Estimation results

Table 1 presents the results of the joint estimation by industries of the production and cost functions (The appendix reports some previous experiments with simpler estimators using the whole sample). The result, from the point of view of production function parameter estimation, is very good. The elasticities of capital, labor and material are sensible and estimated with precision. Returns to scale are not far from unity, with the only exception sector 10. Coefficients on capital, which most estimators have difficulties estimating with variables in differences, seem particularly well estimated. Columns 6 and 7, which report the elasticities for capital and labor scaled by their sum (value added elasticities), show that capital roughly explains from a quarter to a third of the sum. It is a remarkable sign of robustness that all these results are obtained for the six sectors without any change in the specification and from relatively small samples.

Column 8 reports the estimates of the elasticity of demand with respect to the own price. Recall that these estimates are structural, in the sense that this is the elasticity which characterises the function, not an estimate of the price sensitivity implicit in the observed markup which would also depend on the particular form of market competion. The elasticities also show sensible values, which range from a value of 7.0 to 1.6. Notice that, under Bertrad competition, these elasticities would imply margins ranging from 14 to 62%. If these elasticities should give an idea of the degree of average product substitutability, the results are apparently not bad: printing products and chemicals would have the highest product differentiation, while transport equipment and metal products the lowest. Food and textiles would occupy an intermediate position. In any case, it is important to notice that these elasticities are only average values in broadly defined industries which are likely to vary enormously across firms. Enlarging the specification to deal with heterogenous intra-industry elasticities is one of the aims of our next steps in research.

The effects estimated for the shifters are quite sensible too. The variable market dynamism works as a nice indicator of shifts in demand, always positive, sizeable and picked up with high precision. This variable may seem a little uninteresting from the point of view of policy consequences but, given its role, one wonders how important the generated biases are when omitted from the specification of simple production function estimates. The rate of growth of advertising shows positive significant effects in all sectors except industry 6, in which it is negative and non-significant. This points out an important role for advertising as a shifter in most of the sectors. It would, however, be interesting to test for a possible endogeneity coming from correlation in advertising changes and anticipated shocks in demand. The insignificant effect of industry 6 also indicates that possible changes through markup effects should be checked (see the discussion on product innovation below).

The effects of innovation should be read as the average impact of the introduction of process and product innovations, respectively. Process innovations are specified as cost-decreasing shifters and hence their impact must be taken as the proportional decrease in cost implied on average by a process innovation. Product innovations are specified as demand shifters and hence their impact must be taken as the average increase in the firm demand implied by the introduction of a product innovation. Coefficients are again sensible and their values, interesting in themselves, are the basis for the welfare calculations. Let's first discuss the values of the estimates.

Process innovations always appear to decrease cost. It is true that the effects are in many cases imprecisely estimated but we expect to improve this with the second-step estimates. Reduction in cost typically seems to be located between 0.5 and 2.5 percentage points of marginal cost The industries with the most important cost reducing process innovations are 3 (Chemicals products) and 8 (Textile, leather and shoes). Product innovation appears to raise demand in four industries. The amount can be understood as the percentage change in quantity that the firm can sell at a given price. The average demand increases because of the introduction of a product innovation range from 3 to almost 10%. The lowest positive increase takes place in industry 3 (Transport equipment) and the highest in industry 1 (Metals and metal products).

The apparently puzzling question is that product innovation appears to decrease demand in the remaining two industries: industry 3 (Chemical products) and industry 8 (Textile, leather and shoes). In the first case, reduction is by 4 percentage points and is statistically significant. In the second, it is by 2 percentage points and it is imprecisely estimated. How can this be explained? The answer is related to the specification of margins. With margins invariant with respect to innovation, the effect should be positive. But with margins positively related to product innovation, the sign of the total demand effect can be negative (see section 2.4). Intuitively, there are two different demand effects: one is the enlargement of demanded quantity because the product has improved; the other is the reduction in demand because product innovation has led to a margin enlargement and hence to a price increase. If the second effect dominates, the total product innovation effect on demand can be negative. Both effects can be separately identified by estimating the system consisting of the production function and the price equation. Once the margin effect is accounted for (see below), the impact of product innovation seems to be non-significant in the case of industry 3 and positive and important (12 percentage points) in industry 8.

Let us present some preliminary estimates of the system consisting of the production function and the pricing equation.Table 2 presents the results corresponding to sectors 1, 3 and 8. The equation for prices adds the possibility of a separate modelling of margin but also presumably a different disturbance. In the first trials, the three reported industries gave more or less sensible results without the need to change anything. However, the results of the other three industries show some signs of lack of identification. A more systematic exploration of this equation is needed. In any case, it is interesting enough that this system works well in the two cases in which the previous system detects varying margins. The specification also reveals significant margin effects just in these two cases. Curiously, margin effects are negative for advertising (advertising would be associated in these two sectors to price reductions).

In Table 3, we employ the cost-reducing and quantity-enlarging estimated effects, together with the elasticity of demand, to estimate welfare effects. Welfare effects are for the moment computed under the assumption of constant margins, and hence only applied to the cases in which we presume that this assumption holds. Formulas, shown in the table, also assume Bertrand pricing. They can be easily deduced by considering the corresponding cost and demand displacements from one period to another, and linearly approximating the changes in demand in the neighborhood of equilibrium. Variations in consumer surplus and profits are given in proportion to current sales before the introduction of the innovation. The numbers reflect static gains, or gains in the period in which the innovations are introduced.

Numbers are perfectly reasonable and show many interesting characteristics. Process innovations imply an average welfare gain of 1.6 percentage points of sales, with two-thirds of this gain being consumer surplus increment and the remaining third the increase in profits. The gains due to product innovations are higher (4 percentage points) but evenly split between consumer surplus and profits.

5. Conclusion.

This paper has carried out an exploration of the use of semi-reduced forms to estimate the parameters of microeconomic production functions. These reduced forms employ information on the demand relationship and the pricing of firms. Estimates use a rich data set which includes the firm-level changes in the price of the output and in the prices paid by the inputs, the introduction of process and product innovations and information on two more demand shifters: the advertising of the firm and market dynamism. Estimates have been carried out by means of joint non-linear GMM estimation of the output and cost/price equations. Results are very good and many implications remain to be exploited.

The main results up to here are as follows. The reduced form for output provides good estimates for the coefficient on capital but prices have to be instrumented with variables close to shadow price changes. On the contrary, the reduced form for average cost produces sensible estimates for the coefficient on prices. The joint estimation of both equations, using a minimum of instruments (shadow prices indicators and user cost of capital), gives highly sensible results. The coefficients on capital are reasonable, returns to scale close to one, and the elasticity of demand with respect to price takes sensible values. The estimates for the effects of demand shifters are equally good and show positive roles in demand enlargement for the market dynamism indicator and variations in advertising. Innovation has an important role: process innovations reduce marginal costs, and product innovations enlarge demanded quantities and, in some cases, are associated to margin changes.

The cost-reducing and quantity-enlarging effects, together with the elasticity of demand, are employed to estimate current period welfare effects of innovation under the assumption of constant margins and Bertrand competition. Process innovations imply an average welfare gain of 1.6 percentage points of sales and two-thirds of this gain is consumer surplus increment. The gains due to product innovations are higher (4 percentage points) but evenly split between consumer surplus and profits.

Data Appendix:

All employed variables come from the information furnished by firms to the ESEE (Encuesta Sobre Estrategias Empresariales) survey, a firm-level panel survey of Spanish manufacturing starting in 1990 and sponsored by the Ministry of Industry. The unit surveyed is the firm, not the plant or establishment, and some closely related firms answer as a group. At the beginning of this survey, firms with fewer than 200 workers were sampled randomly by industry and size strata, retaining 5%, while firms with more than 200 workers were all requested to participate, and the positive answers represented a more or less self-selected 60%. To preserve representation, samples of newly created firms were added to the initial sample every subsequent year. At the same time, there are exits from the sample, coming from both death and attrition. The two motives can be distinguished and attrition was maintained to sensible limits. Composition in terms of time observations of the whole unbalanced panel sample employed here is shown in Table A.1. Table A.2 provides descriptive statistics and Table A.3 details the industry breakdown, from which the main estimates use industries 1,3,6, 7,8 and 10.

Definition of variables

Advertising: Firm's advertising expenditure deflated by the consumer price index.

Averagecost: Firm's total costs divided by output.

Capital : Capital at current replacement values is computed recursively from an initial estimate and the data on current firms' investments in equipment goods (but not buildings or financial assets), actualised by means of a price index of capital goods, and using sectoral estimates of the rates of depreciation. Real capital is then obtained by deflating the current replacement values.

Hours per worker: Normal hours of work plus overtime minus lost hours per worker.

Industry dummies: Eighteen industry dummies.

Industry price decrease: Dummy variable that takes the value 1 when the firm reports an own-price decrease which has been motivated by a reduction of prices of competitors in its main market.

Industry prices: Industry indices computed for 114 sectors and assigned to the firms according to their main activity.

Labour: Number of workers multiplied by hours per worker.

Market dynamism: Weighted index of the market dynamism reported by the firm for the markets in which it operates. The index can take the values $0<d<0.5$ (slump), $0.5<d<1$ (expansion) and $d=0.5$ (stable markets). Included in regressions in differences from 0.5.

Materials: Intermediate consumption deflated by the price of materials.

Output: Goods and services production. Sales plus the variation of inventories deflated by the firm's output price index.

Price of materials: Paasche-type price index computed starting from the percentage variations in the prices of purchased materials, energy and services reported by the firms. Divided by the consumer price index except when used as a deflator.

Price of the output: Paasche type price index computed starting from the percentage price changes that the firm reports to have made in the markets in which it operates.

Product innovation: Dummy variable that takes the value 1 when the firm reports the accomplishment of product innovations.

Process innovation: Dummy variable that takes the value 1 when the firm reports the introduction of a process innovation in its productive process.

Utilisation of capacity: Yearly average rate of capacity utilisation reported by the firm.

User cost of capital: Weighted sum of the cost of the firm values for two types of long-term debt (long-term debt with banks and other long-term debt), plus a common depreciation rate of 0.15 and minus the rate of growth of the consumer price index.

Wage: Firm's hourly wage rate (total labour cost divided by effective total hours of work). Divided by the consumer price index.

Appendix

In this appendix we briefly comment on some previous estimates for the whole sample.

Table B1 reports the main results of the direct conventional production function estimates. Capital and utilisation of capacity always tend to obtain close coefficients (a bit lower for capital) and we opt for reporting the results for the constrained variable (variation in) "used capital." OLS results are not bad. Capital attracts a statistically significant coefficient, although somewhat small: 19% of the sum of the capital and labour elasticities (see Value added elasticities). Returns to scale, as is usual in OLS estimates, turn out to be diminishing (elasticity of scale is less than 0.8). The use of different ways of deflating the output measure has a small impact on the estimates. It is worthy of noting that the main impact is not on the elasticity estimates, but on the constant and the innovation effect estimates.

IV estimation is carried out with conventional instruments. Labour and materials are instrumented, in a GMM framework, with their levels lagged two periods at each cross-section. The number of lags used can be increased without important changes. The variable capital plus utilisation of capacity is instrumented using the capital growth rate at t-1. Notice that this is a valid instrument under the assumption that capital is a predetermined variable, which can also be considered to take utilisation of capacity as endogenous. The Sargan test of overidentifying restrictions points to the validity of the instruments. The IV estimation increases all coefficients, but the coefficient on materials and the coefficient on capital quite a bit more. Precision, however, is low. Returns to scale now tend to be increasing (elasticity of scale is 1.08 at the estimate which uses individual prices). The estimate which uses individual prices now seems to be more sensible, mainly providing a better account of the impact of innovation.

We conclude that conventional estimators in differences seem to give estimates that are not bad when used with enough quality data and slightly better estimates if firm-level prices are available. However, neither the OLS estimates nor the IV estimates are fully convincing. The IV estimate is probably the closest to reliable values, but quite imprecise.

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Table 1
Estimating the parameters of the production and cost functions
Joint nonlinear GMM estimates[1,2]

Industry	No. of firms	Elasticities ε_K	Elasticities ε_L	Elasticities ε_M	Returns to scale	Value added elasticities K	Value added elasticities L	Price elasticity η	Shifters: Process innovation	Shifters: Product innovation	Shifters: Advertising	Shifters: Market dynamism
1. Metals and metal products	168	0.079	0.235	0.627	0.941	0.252	0.748	6.959	0.003	0.096	0.029	0.214
		(0.021)	(0.041)	(0.070)	(0.049)	(0.075)	(0.075)	(2.454)	(0.005)	(0.036)	(0.016)	(0.071)
3. Chemical products	173	0.073	0.147	0.680	0.900	0.331	0.669	2.365	0.023	-0.041	0.043	0.106
		(0.020)	(0.033)	(0.057)	(0.062)	(0.117)	(0.117)	(0.527)	(0.006)	(0.016)	(0.012)	(0.030)
6. Transport equipment	88	0.076	0.235	0.645	0.956	0.244	0.756	6.469	0.006	0.028	-0.017	0.100
		(0.019)	(0.044)	(0.077)	(0.065)	(0.079)	(0.079)	(1.315)	(0.007)	(0.028)	(0.015)	(0.047)
7. Food, drink and tobacco	234	0.043	0.086	0.702	0.832	0.335	0.665	3.744	0.007	0.085	0.024	0.188
		(0.013)	(0.028)	(0.051)	(0.072)	(0.185)	(0.185)	(1.073)	(0.005)	(0.021)	(0.013)	(0.039)
8. Textile, leather and shoes	214	0.058	0.186	0.625	0.869	0.238	0.762	3.084	0.015	-0.022	0.055	0.166
		(0.028)	(0.031)	(0.067)	(0.066)	(0.124)	(0.124)	(1.114)	(0.006)	(0.023)	(0.016)	(0.035)
10. Paper and printing products	101	0.093	0.167	0.494	0.754	0.359	0.641	1.571	0.007	0.064	0.013	0.098
		(0.029)	(0.047)	(0.059)	(0.111)	(0.160)	(0.160)	(0.423)	(0.008)	(0.022)	(0.009)	(0.026)

[1] First-step standard errors in parentheses, robust to arbitrary autocorrelation over time and heteroskedasticity across firms.
[2] Orthogonality conditions for both equations: innovation dummies (process and product), advertising, market dynamism, utilization of capacity, lagged user cost of capital (own and rivals). Orthogonality conditions for equation on output: hours of work, rival's price decrease; Orthogonality equations for equation on cost: wage, price of materials.

Table 2
Estimating the parameters of the production function and price equation
Joint nonlinear GMM estimates[1,2]

Industry	No. of firms	Elasticities ε_K	ε_L	ε_M	Returns to scale	Value added elasticities K	L	Price elasticity η	Shifters: Process innovation	Product innovation[3]	Advertising[3]	Market dynamism
1. Metals and metal products	168	0.072	0.191	0.635	0.898	0.273	0.727	12.199	0.004	0.129	0.003	0.377
		(0.016)	(0.028)	(0.054)	(0.052)	(0.083)	(0.083)	(3.691)	(0.004)	(0.054)	(0.017)	(0.090)
										-0.002	-0.004	
										(0.005)	(0.003)	
3. Chemical products	173	0.074	0.076	0.627	0.777	0.493	0.507	3.306	0.024	-0.013	0.022	0.177
		(0.016)	(0.016)	(0.048)	(0.062)	(0.184)	(0.184)	(0.657)	(0.005)	(0.015)	(0.008)	(0.032)
										0.017	-0.012	
										(0.008)	(0.005)	
8. Textile, leather and shoes	214	0.038	0.127	0.616	0.782	0.230	0.770	13.886	0.011	0.121	0.042	0.566
		(0.015)	(0.025)	(0.050)	(0.078)	(0.135)	(0.135)	(3.726)	(0.005)	(0.058)	(0.021)	(0.125)
										0.016	-0.012	
										(0.007)	(0.004)	

[1]First-step standard errors in parentheses, robust to arbitrary autocorrelation over time and heteroskedasticity across firms.
[2] Orthogonality conditions for both equations: innovation dummies (process and product), advertising, market dynamism, utilization of capacity, lagged user cost of capital (own and rivals). Orthogonality conditions for equation on output: hours of work, rival's price decrease; Orthogonality equations for equation on cost: wage, price of materials.
[3]First-line coefficients are effects on demand, the second line effects on margin

Table 3

Welfare effects of innovation (in proportion of current sales)[1,2]

	Process innovation			Product innovation		
	Δcons. surplus	Δfirm profits	Δtotal	Δcons.r surplus	Δfirm profits	Δtotal
	$\frac{c-c\prime}{c}+\frac{1}{2}\eta(\frac{c-c\prime}{c})^2$	$\frac{\eta-1}{\eta}(\frac{c-c\prime}{c})-(\frac{c-c\prime}{c})^2$		$\frac{1}{\eta}\left[\frac{q\prime-q}{q}+\frac{1}{2}(\frac{q\prime-q}{q})^2\right]$	$\frac{1}{2}(\frac{q\prime-q}{q})$	
1. Metals and metal products	0.003	0.003	0.006	0.014	0.014	0.028
3. Chemical products	0.024	0.013	0.036	-	-	-
6. Transport equipment	0.006	0.005	0.011	0.004	0.004	0.009
7. Food, drink and tobacco	0.007	0.005	0.012	0.024	0.023	0.046
8. Textile, leather and shoes	0.015	0.010	0.025	-	-	-
10. Paper and printing products	0.007	0.002	0.010	0.042	0.041	0.083

[1]Computed with the effects reported in Table 1. Product innovation effects are not computed for sectors 3 and 8.

[2] $(\frac{c-c\prime}{c})$ = proportional change in marginal cost, $(\frac{q\prime-q}{q})$ = proportional change in output, η = elasticity of demand

Table A1. Sample detail

Nº of years in sample	Nº of firms	Observations
3	230	690
4	215	860
5	204	1020
6	150	900
7	115	805
8	143	1144
9	142	1278
10	209	2090
Total	1408	8787

Table A2. Variable descriptive statistics

	Mean	St. dev	Min	Max
Dependent Variables				
Output	0.031	0.239	-2.6	2.4
Average cost	0.021	0.154	-1.2	1.1
Explanatory Variables				
Advertising	0.023	0.903	-2.0	2.0
Capital	0.081	0.313	-2.1	7.3
Hours per worker	-0.001	0.065	-1.7	1.7
Industry price decrease	0.058	0.234	0	1
Industry prices	0.022	0.034	-0.21	0.4
Labour	-0.008	0.190	-2.8	1.7
Market dynamism	0.504	0.320	0	1
Materials	0.021	0.350	-3.3	5.4
Price of materials	0.035	0.060	-0.5	0.7
Price of the output	0.014	0.056	-0.7	0.7
Process innovation	0.332	0.472	0	1
Product innovation	0.266	0.442	0	1
User cost of capital	0.135	0.046	0.1	0.4
Utilization of capacity	0.001	0.191	-2.3	2.9
Wage	0.054	0.190	-1.5	2.4
Industry dummies				
Ferrous and non-ferrous metals	0.022	0.146	0	1
Non-metallic mineral products	0.075	0.263	0	1
Chemical products	0.071	0.256	0	1
Metal products	0.098	0.298	0	1
Agricultural and ind. machinery	0.053	0.225	0	1
Office and data processing machin.	0.009	0.093	0	1
Electrical goods	0.076	0.264	0	1
Motor vehicles	0.045	0.207	0	1
Other transport equipment	0.020	0.138	0	1
Meats, meat preparation	0.031	0.174	0	1
Food products and tobacco	0.117	0.321	0	1
Beverages	0.021	0.143	0	1
Textiles and clothing	0.116	0.321	0	1
Leather, leather and skin goods	0.032	0.176	0	1
Timber, wood products	0.065	0.246	0	1
Paper and printing products	0.073	0.260	0	1
Rubber and plastic products	0.053	0.224	0	1
Other manufacturing products	0.025	0.155	0	1

Table A3. Industry definitions and equivalences

	Industry breakdown		ESEE clasiffication
1	Ferrous and non-ferrous metals and metal products	1+4	Ferrous and non-ferrous metals + Metal products
2	Non-metallic minerals	2	Non-metallic minerals
3	Chemical products	3+17	Chemical products + Rubber and plastic products
4	Agricultural and ind. machinery	5	Agricultural and ind. machinery
5	Office and data-processing machines and electrical goods	6+7	Office and data processing machin. + Electrical goods
6	Transport equipment	8+9	Motor vehicles + Other transport equipment
7	Food, drink and tobacco	10+11+12	Meats, meat preparation + Food products and tobacco + Beverages
8	Textile, leather and shoes	13+14	Textiles and clothing + Leather, leather and skin goods
9	Timber and furniture	15	Timber, wooden products
10	Paper and printing products	16	Paper and printing products

Table B1 Conventional production function estimates[1]

Dependent variable: Output[2]					
Sample period: 1992-1999					
Method of estimation[3]		OLS	OLS	IV	IV
Independent variables					
	Constant	0.015 (0.002)	0.008 (0.002)	0.006 (0.009)	-0.003 (0.010)
	Process innovation dummy	0.016 (0.004)	0.012 (0.003)	0.013 (0.004)	0.007 (0.004)
	Capital+Utilization of capacity	0.066 (0.012)	0.069 (0.011)	0.177 (0.124)	0.210 (0.128)
	Labour	0.277 (0.027)	0.289 (0.026)	0.327 (0.167)	0.328 (0.174)
	Materials	0.429 (0.022)	0.43 (0.022)	0.577 (0.078)	0.593 (0.080)
	Time dummies	included	included	included	included
	Industry dummies				
Statistics					
	Instruments			Capital growth rate at t-1 Labour and materials t-2 lagged levels at each cross-section	
	Sigma	0.108	0.107	0.120	0.121
	Residuals' first-order correlation[4]	(-8.4)	(-8.5)	(-7.7)	(-8.0)
	Residuals' second-order correlation[4]	(-1.6)	(-2.0)	(-0.3)	(-0.3)
	Sargan test (degrees of freedom)			15.5 (14)	17.2 (14)
	No. of firms	1,408	1,408	1,408	1,408
	No. of observations	5,971	5,971	5,971	5,971
Elasticities					
	Returns to scale	0.772	0.788	1.081	1.131
	Value added elasticities:				
	Capital	0.191	0.193	0.351	0.390
	Labor	0.809	0.807	0.649	0.610

[1]All non-dummy variables in (log) growth rates.
[2]First and third columns deflated by individual prices, second and fourth columns deflated by industry prices.
[3]Robust standard errors in parentheses.
[4]Arellano-Bond test value.