Panel-Data Estimates of the Production Function and the Revenue Function: What Difference Does it Make?[#]

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Abstract

The lack of individual firm information on output prices is a major problem in the econometrics of production. In particular, one would expect that it may account for a significant share of the large discrepancies found in productivity panel-data studies between the cross-sectional and time-series estimates of capital and scale elasticities (Klette and Griliches, 1996). For this study, we were able to obtain individual information on output price indices—as well as on capacity utilization rates—for a balanced panel of about 450 French manufacturing firms over four years and an unbalanced panel of 675 Spanish manufacturing firms over nine years. However, whether we rely on OLS or IV panel-data estimation methods, estimating the revenue function (using a nominal output measure) or the production function proper (using a real output measure) makes little or very little difference on our results. The biases due to other sources of specification errors are probably more important. Needless to say, the availability of individual output price information remains essential to investigate and model firm behavior thoroughly.

Key words: production function; revenue function; panel data; estimation bias; specification errors; price dispersion; capacity utilization.
JEL classification: C23; D24.

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"We have not succeeded in answering all our problems. The answers we have found only serve to raise a whole set of new questions. In some ways we feel we are as confused as ever, but we believe we are confused on a higher level and about more important things".
[Sitert i Øksendal (1985)] - One of Tor Jakob Klette's favourite quotes.

1. Introduction.

The lack or unavailability of individual data on firms' output price indices is one of the major problems in the micro-econometric analysis of firms' behavior, obviously as regards price-setting behavior but also production, cost and factor demand functions. For the estimation of the production function —the only focus of our attention here— the standard practice consists in deflating the nominal output of the firm (or its value added) by replacing the unknown individual price index with the price index for the firm industry. This is an imperfect solution, even when the output price indices are available at a very detailed industry classification level. Following Marschak and Andrews (1944) in their pioneer analysis of identification issues in estimating production functions, Klette and Griliches (1996) make the point that such an approach cannot prevent biases when the changes in firm prices within industries (even narrowly defined) are substantially dispersed and correlated with the changes in labor and capital (and other production factors). In particular, Klette and Griliches suggest that these biases could be one of the reasons for the observed disparities between the different types of estimates of labor and capital elasticities using firm panel data. Our paper seeks to determine whether these propositions are true, knowing that other sources of bias are also potentially very important.

To what extent does the absence of individual output prices explain why the panel data estimates which only or mainly rely on the time changes of the variables (i.e., on the longitudinal or "time series" dimension of the data) are often fairly implausible, leading among other things to very low capital elasticities and rather sharply diminishing returns to scale? To put it differently, can we relate the fact that the panel data estimates relying mostly on the individual differences in the levels of the variables (the "cross-sectional" dimension of the data) are generally more reasonable, to the fact that these estimates are not estimates of the production function *stricto sensu*, but estimates of the "revenue function" that do not require the knowledge of output prices? Can information on firm output prices thus narrow the discrepancies between these two major types of panel data estimates?

We seek to answer these questions by directly examining the evidence, taking advantage of the fact that we have been able to obtain information on firm output price indices for two panel data samples: a balanced sample for 468 French manufacturing firms over the period 1994-97, and an unbalanced sample for 675 Spanish manufacturing firms over the period 1991-1999.[1]

In our investigation, we have also been able to take advantage of information on firm capacity utilization rates, and not only on firm output prices. Indeed, information on capacity utilization is usually lacking in studies on firm panel data. Ignoring changes in firm capacity utilization rates (as well as the correlated changes in the firm's average

[1] Until now, the study by Abbott (1991) is the only one, to our knowledge, that has tried to perform a very similar investigation. It relied, however, on a very small sample of only 40 U.S. establishments in the Portland cement industry, for which the author was able to compute average output prices using direct data on the quantities of the different varieties of Portland cement they produced and on the corresponding shipments, available in the 1972, 1977, and 1981 U.S. Census of Manufacturing. As these prices were available only for three years, however, the author was unable to produce estimates based on first differences, as we do, but only estimates based on five and ten year differences (which are only reported in chapters 7 and 8 of his Ph.D. dissertation – Abbot 1987).

number of hours worked per employee) is viewed as another serious source of bias in time-series type estimates, and as a reason for their divergence from cross-sectional type estimates. The two sources of bias, the lack of data on prices and on capacity utilization at the firm level, are fairly similar, although they reflect different economic behaviors.[2] In order to assess the specific impact of the dispersion of output price changes on production function estimates, and not to confound it with the impact of the variability in capacity utilization, we deemed it better, since we could do it, to take capacity utilization directly into account in most of the estimates we will be reporting.

In the same spirit, we have widely experimented in trying to take into account the three general sources of potential biases in panel data estimates, known as heterogeneity, endogeneity, and (random) errors in variables. Being able to directly rely on output price information to assess the related biases, even if this information is far from perfect, put us in a more satisfactory situation than when we try to indirectly control for heterogeneity, endogeneity and errors in variables. In order to do the later we are led to rely on instrumental variables (IV) estimation methods and specifically on the generalized method of moments (GMM) applied to panel data. These methods are based on different sets of exogeneity hypotheses (or "orthogonality conditions") that usually produce estimates which are very vulnerable to other types of specification errors, and very imprecise on samples of moderate size such as ours.

In our study, we thus basically compare various sets of estimates of a simple Cobb-Douglas production (or revenue) function in which we do not deflate output (or deflate it

[2] They are two important causes of miss-measurement in firm productivity changes, corresponding to the omission of two critical, but essentially time-varying, variables in the firm production function. They are therefore both very likely to affect the estimates of factor elasticities, but mostly so in the time-series dimension of the data.

only by an industry output price index in keeping with standard practice) and in which we deflate output by our firm output price variable (or include it as an additional control variable in the production function). We begin by looking at the ordinary least squares (OLS) traditional panel data estimates, and then proceed by considering various panel data IV estimates with internal and/or external instrumental variables.

Our results do not corroborate initial expectations. Whatever our estimation methods, the introduction of individual output prices into the production function does not in general markedly modify the capital, labor and scale elasticity estimates. Estimating a revenue function instead of a proper production function thus does not seem to be a major cause of divergence between cross-sectional and time series estimates of the production function.[3] It is likely that the main culprits for such divergence remain errors in variables and other types of complex specification errors, which are not well taken into account by the IV (or GMM) panel data estimators and tend to be exacerbated in the time-series dimension of the data, generating larger biases in that dimension than in the cross-sectional dimension.[4],[5]

In Section 2 of the paper, we follow Klette and Griliches (1996) to illustrate the risks of biases due to the absence of information on firm output prices when estimating

[3] Note that this conclusion is not the one reached by Abbot (1991). Although he cannot effectively regress on first differences using the data available to him (cf. footnote 1), he makes the case that if he had been able to make such regressions they would probably have produced results comparable to the cross-sectional estimates. His argument does not seem very strong, and his estimates based on five and ten year differences (reported in chapters 7 and 8 of his Ph.D. dissertation – Abbot 1987) are very similar to ours, thereby weakening his conjecture.

[4] On these points, see in particular Mairesse (1990) and Griliches- Mairesse (1998).

[5] Recently, a paper by Ornaghi (2005) has used a sample coming from the same Spanish survey data than ours to also address the question of the likely differences in parameter estimates of the production function when one uses industry or firm output price deflators. He only compares GMM estimates on differenced equations, both for gross output and value added, obtaining a marginal improvement in the estimated elasticity of scale when individual price indices are used. The elasticity of capital is, however, very small in all his estimates. These results, when situated in a broader perspective, do not contradict our findings, although the author seems more optimistic than we are in interpreting them.

the production function.[6] In Section 3, we document and discuss the results obtained for the two samples of French and Spanish manufacturing firms. We briefly conclude in Section 4.

2. Implications of the absence of individual output prices

The effects of the absence of individual output prices on production function estimates are not difficult to analyze if we assume that firms operate in imperfectly competitive markets where actual price differences reflect the differentiation of their products. For simplicity's sake, let us assume that the production function of firm *i* in year *t* is a Cobb-Douglas function which can be written in the form of the standard (log) linear regression:

$$q_{it} = a_t + \alpha k_{it} + \beta l_{it} + u_{it} \qquad \text{with } \mathrm{i} = 1, \cdots, \mathrm{N} \text{ and } \mathrm{t} = 1, \cdots, \mathrm{T} \qquad (1)$$

where q, k, and l are respectively the logs of volumes of output (measured by value-added), capital, and labor; u denotes the error or disturbance term, and a_t the (log) autonomous technical-progress coefficients (or log average total factor productivity); and α, β and $\mu=\alpha+\beta$ are the capital, labor and scale elasticities of interest.

An underlying assumption in this formulation is that we effectively use a real or volume measure of output at the individual firm level. As we usually lack firm information on the prices of output, the volume of the firm output is unknown and usually proxied by the nominal output deflated by an output price index of the firm industry. Instead of q_{it} = (y_{it}-p_{it}), we therefore measure (y_{it}-p_{St}), where y_{it} is nominal (log) output,

[6] See also Griliches- Mairesse (1984 and 1998). Melitz (2000) uses basically the same framework that Klette and Griliches (1996), with similar conclusions on the likely biases in estimating the revenue function and not the production function when there is lack of information on individual firm output prices. His emphasis, however, is on the proper measurement of total factor productivity at the firm level, not the estimation of the production function parameters.

and p_{it} and p_{St} are, respectively, the (log) price index of firm *i* and the (log) price index of industry *S* (to which firm *i* belongs).While we should estimate the equation (1), the equation we usually estimate is in fact:

$$(y_{it} - p_{St}) = q_{it} + (p_{it} - p_{St}) = a_t + \alpha k_{it} + \beta l_{it} + v_{it} \qquad (2)$$

where the firm (log) price deviation to the industry (log) price (i.e., the log of the firm price relative to the industry price) is embedded in the disturbance term:

$$v_{it} = (p_{it} - p_{St}) + u_{it} \qquad (3).$$

It is thus fairly obvious that the estimates of capital, labor and scale elasticities α, β, and $\mu=\alpha+\beta$, will be biased if the firm output prices are (1) significantly dispersed within industry and (2) significantly correlated within industry with the production factors. This bias problem is a priori hard to address by means of an instrumental-variables estimation method. Finding valid instruments indeed seems particularly difficult, as any variable correlated with labor and capital (and the other production factors) will probably be correlated with the output prices as well, via the firm's production function and demand function.

Let us more precisely suppose that the firm's demand function results from the imperfect substitutability of its products with those of competing firms in the same industry and that it can be written simply in the form of a (log) linear regression:

$$(q_{it} - q_{St}) = \eta(p_{it} - p_{St}) + w_{it} \qquad (4)$$

where $(q_{it}\text{-}q_{St})$ is the (log) share of the firm real output in that of the industry, $(p_{it}\text{-}p_{St})$ the (log) of the firm price relative to that of the industry, and η the price elasticity of demand, which is, in principle, negative ($\eta<0$). This function means that the firm, because of product differentiation, can capture an additional share of the industry market by lowering its price, a 1% reduction in its relative price (p_{it}-p_{St}) boosting its market share (q_{it}-q_{St}) by -η% , other things equal. The term w_{it} denotes the other demand determinants and shifters, and the various demand shocks that may influence demand for the firm's products, independent of price changes: they include investments in research and product innovation, advertising and marketing expenditures, changes in consumer income and tastes, and so on.

The inverse demand function, expressing relative price as a function of the demand shocks and the firm market share in real or value terms (q_{it}-q_{St}) or (y_{it}-y_{St}) = (q_{it}-q_{St})+(p_{it}-p_{St}) , can be written equivalently as:

$$p_{it} - p_{St} = \eta^{-1}(q_{it} - q_{St} - w_{it}) = (1+\eta)^{-1}(y_{it} - y_{St} - w_{it}) \qquad (5).$$

Through substitution in the estimated production function, we can then formulate the latter as:

$$(y_{it} - p_{St}) = \omega^{-1} \ (a_t + \alpha k_{it} + \beta l_{it}) + \varepsilon_{it} \qquad (6)$$

where $\varepsilon_{it} = (\eta^{-1} q_{St} + \omega^{-1} u_{it} + \eta^{-1} w_{it})$ and $\omega = \eta/(1+\eta)$ is the margin or markup ratio (or markup power parameter). This new expression of the production function as estimated in practice as a revenue function (in output-value terms or in value terms deflated by an industry price index) gives us an idea of the potential size of the biases that may influence the factor-elasticity estimates.[7] It suggests that the revenue function

[7] It also shows that the disturbance term ε is affected both by supply shocks u and demand shocks w; hence only variables impervious to both types of shocks can serve as valid instruments for the production function in output value terms. We also note that if we explicitly introduce the industry-output variable q_{St} into this production function, it becomes possible, in theory, to identify and estimate the demand-elasticity

estimates of labor, capital and scale elasticities could be downward-biased relatively to the production-function estimates proper. Such underestimation would be inversely proportional to the markup ω, and thus larger for a smaller absolute price elasticity of demand; it could be, for example, of about 25% for a price elasticity η on the order of -4 and a markup ω on the order of 1.25.[8]

These conclusions do not apply, of course, unless the analytical framework that we have just described is suitable, and especially unless the hypothesis of a firm demand function as specified above is satisfactory. We need to make three important observations in this respect, regarding three cases where the correlation between output prices and production factors would be negligible, and hence the ensuing biases as well.

The first observation concerns the case of (near) perfect competition where the price elasticity of demand tends to a very high value, and the margin rate toward zero (the markup ratio toward unity). Here, the biases would be negligible and the "between-firms" dispersion of changes in actual individual prices would essentially reflect (random) measurement errors. This situation, however, does not seem very realistic, except in some highly competitive industries and perhaps over the long run.

The second observation concerns the case where the relation of the changes in real output with the changes in output prices, as expressed by the firm demand function (estimated in the time dimension of the data), is weak relative to that with the

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parameter η, and therefore the markup parameter ω; from that, we can infer unbiased estimates of capital elasticity α and labor elasticity β, even lacking information on individual prices. That is in fact the solution suggested by Klette and Griliches (1996) and also implemented, for example, in Crépon, Desplatz, and Mairesse (1999).

8 These orders of magnitude are those preferred by Crépon, Desplatz, and Mairesse (1999) for a sample of French manufacturing firms comparable to the French sample used here.

demand shocks and its other determinants (the changes in w_{it}). In this case the simple correlation (unconditional upon the other demand determinants) between output prices and output volumes will be small and hence also the transmitted correlation between output prices and the production factors. The latter will therefore be fairly unimportant compared to the correlations between the supply shocks u_{it} and the production factors, due to other likely production-function specification errors. This is the more plausible reason why our panel data estimates actually display little change—as we will observe—when we are able to take into account the individual output price information.

The third observation is particularly important in the context of panel data, since it provides a justification for estimating the production function or revenue function from the levels of the variables and not only from their changes (or log first differences), irrespective of whether output is expressed in value or volume terms. In the levels of the variables, the estimation of a production function in terms of "physical quantities" (or some other natural units) is in fact meaningless—unless we confine the analysis to a very precisely defined industry where the goods are so homogeneous that firm outputs can be well measured and compared across firms in this way.[9] In the general case where the goods produced are heterogeneous, we can only expect to find meaningful estimates of the production function or revenue function, when firm outputs are measured in units of "volume" (say in euros) at the prices of the goods for a given base-year, or in units of "value" (say in euros) at the prices of the different goods in the current year. However, the price differences across firms will be by construction zeros in the chosen base-year, and it is plausible that the correlations across firms, in any other year, between price

[9] This criticism dates back to the first studies by Douglas estimating the (Cobb-Douglas) production function on cross-sectional firm data instead of aggregate series as before. It has been vigorously reiterated since, notably by Phelps-Brown (1957).

differences and real output differences will remain small for similar reasons as those suggested above (idiosyncratic demand shocks and other firm specific determinants being likely to prevail). Altogether we should not be surprised that estimating the production or the revenue function (i.e., whether we deflate output by individual prices or not) makes little difference on the results when they rely mainly on cross-sectional dimension and do not control adequately for individual firm correlated effects.

3. Estimating a production function with and without individual output prices.

3.1 Samples, variables, model specifications and estimators.

Our samples consist of a balanced panel of 468 French firms for the four year period 1994-1997, and an unbalanced panel sample of 675 Spanish firms for the nine year period 1991-1999. Details on the samples' origin and construction and on the exact definition of the variables can be found in the working paper version of this article.[10] The main feature of the two samples is the availability at the firm level of information on output price changes, as well as on the rates of capacity utilization. Basically what we do is systematically compare a large variety of estimates of the simple Cobb-Douglas production function, generally including as a right-hand side variable the firm rate of capacity utilization, and using respectively as the dependent variable the firm value added undeflated (y_{it}), deflated by an industry output price index(y_{it}-p_{St}) and deflated by the firm output-price index (y_{it}-p_{it}). We also experiment by including the firm

[10] Our samples consist mainly of medium-sized firms in the two countries with a mean size of 275 and 198 employees in the case of France and Spain, respectively. Although the proportion of largest firms is not so different in the two samples (the twentieth percentiles are 869 and 739 employees in the case of France and Spain, respectively), the Spanish sample has relatively more small firms, which agrees with the overall size distributions of manufacturing firms in the two countries. The working version of the paper is available on request to the authors.

output-price index as a right-hand side variable (with value added undeflated as the dependent variable).

Precisely, we are estimating the linear regression of the following form:

$$(y_{it}^{*} - l_{it}) = a_t + \alpha(k_{it} - l_{it}) + (\mu - 1)l_{it} + \delta uc_{it} + \gamma p_{it}^{*} + u_{it} \qquad (7)$$

where $(y_{it}^{*} - l_{it})$ is log of firm labor productivity measured as value added per worker – undeflated or deflated as specified in each case; $(k_{it} - l_{it})$ the log of physical capital per worker at the beginning of the year, measured by the gross book value in the firm balanced sheet (adjusted for inflation); l_{it} the log of labor expressed as the number of employees; uc_{it} the log of the rate of utilization of capacity as declared by the firm; p_{it}^{*}, as specified in each case, either the log of the industry price index (available from the national accounts) or the firm price index as declared by the firm. The year coefficients a_t account for technical change (and other general time influences on productivity, such as arising from the general business cycle, and not captured by firm capacity utilization rates); α, $\beta = (\mu - \alpha)$ and μ are respectively the capital, labor and scale elasticity parameters. We are generally assuming, as is usual in panel data econometrics, that the disturbance term u_{it} can be decomposed in two error components $u_{it} = u_i + v_{it}$, where u_i represents an individual firm effect, supposedly invariant over time, and v_{it} is the idiosyncratic firm and time-specific disturbance, supposedly uncorrelated across firms and over time. We also consider, however, the possibility that v_{it} is a first-order serially correlated error term of the form $v_{it} = \rho v_{it-1} + e_{it}$ (with e_{it} uncorrelated across firms and over time).

On total, we will systematically examine the results of the six following regressions 1) a "revenue" function ($y^*_{it} = y_{it}$ and $\delta = \gamma = 0$); 2) a revenue function controlling for utilization of capacity ($y^*_{it} = y_{it}$ and $\gamma = 0$); 3) a production function using the industry output price p_{St} for deflation ($y^*_{it} = y_{it} - p_{St}$ and $\gamma = 0$); 4) a production function using the firm output price p_{it} for deflation ($y^*_{it} = y_{it} - p_{it}$ and $\gamma = 0$); 5) the inclusion of p_{St} as a right-hand variable ($y^*_{it} = y_{it}$ and $p^*_{it} = p_{St}$); and 6) the inclusion of p_{it} as a right-hand variable ($y^*_{it} = y_{it}$ and $p^*_{it} = p_{it}$).[11]

Panel data estimators of these types of regressions are aimed at addressing three main possible causes of biases: the presence of individual heterogeneity (or unobserved firm effects), embodied in the u_i component of the disturbance term, possibly correlated with all or part of the explanatory variables; the likely endogeneity of some variables because of their simultaneous determination, or their potential correlation with the past and contemporaneous component v_{it} of the disturbance; and the presence of errors in variables, which raises another source of correlation with the disturbance. We are considering two types of estimators which try to control for some of sources of biases.[12] We begin with the traditional OLS estimators in levels and first differences. First differences controls for individual heterogeneity simply by removing the firm effects u_i from the equation. We then experiment with a series of IV or GMM panel data estimators, which endeavor to correct for the two other sources of potential biases by

[11] In the IV estimates, we replace 5) and 6) by the following alternatives: 5') the same as 5 but treating p_{it} as an exogenous variable; and 6') the same as 6 but treating p_{it} as a variable contemporaneously correlated with the error.

[12] Up-to-date reviews of panel data estimators can be found, for example, in Arellano and Honore (2001), and Arellano (2003).

using appropriate instruments: basically the lagged variables in levels if the production function equations are in first differences, and the lagged variables in first differences if the production functions equations are in levels. For the Spanish sample we are also able to use two external instruments: the average wage and an index of the prices of intermediate consumption. This sample is also large enough to allow us to investigate the possibility of a first-order serially correlated idiosyncratic disturbance v_{it} by instrumenting the production function written in terms of quasi-differences by the lagged variables in first differences.

Table 1 reports some simple descriptive statistics concerning means, dispersion and correlations among the variables, which we comment on in the next subsection. Table 2 reports the OLS estimates; Table 3 the basic IV estimates; Tables 4 the IV estimates in quasi-differences and Table 5 the estimates using external instruments.

3.2 Descriptive statistics.

Let us comment on Table 1. The average growth rates of value added, the number of employees, physical capital stock and the degree of capacity utilization are higher in the Spanish sample than in the French sample, which is in accordance with the good overall performance of the Spanish economy in the 1990's. Average growth in firm output prices is also faster in the Spanish sample (2.2%) than in the French one (0.3%), roughly corresponding to what we see also on the industry output prices. As anticipated, however, the growth rates in output prices are significantly more dispersed at the firm level than at the industry level.

The pattern of correlations is on the whole similar in both samples, and concurs well with what could be expected. Changes in value added are positively and significantly correlated with the changes in labor, capital and capacity utilization. Changes in capital are also positively correlated with those in labor (and negatively with capacity utilization in the French sample). As should be, firm output price changes are positively and significantly correlated with industry price changes, although more strongly so in the French sample than in the Spanish sample.

More interestingly, firm output price changes are also positively and significantly correlated with the changes in capacity utilization in both samples. This is a nice confirmation of the informative content of the variables, because firms are likely to raise prices as capacity is increasingly used and marginal cost rises. Finally, firm price changes are also positively correlated to value added changes. No particular sign is expected for this simple (overall) correlation, since changes in nominal value added can be positively related to price changes, because of the effects of other demand factors w_{it} (and of being undeflated), even though they are negatively related to these prices changes conditionally on the other factors through the firm demand relationship (with (η<-1).

3.3 OLS panel data estimates.

Table 2 displays the OLS panel data estimates in the "levels" of the variables (which treats the cross-sectional and time-series dimensions of the data in the same way), and in the (log) "first differences" of the variables (which relies only on the time-series dimension of the data, removing its cross-sectional dimension). Both in levels and first differences the estimated elasticities of capital and scale, and hence of labor, are quite close in the French and Spanish samples: respectively, of about 0.20– 0.25, 1.05–1.10 and 0.80– 0.85 in levels; and all three estimates sharply decreasing in first differences to about 0.05– 0.10, 0.65– 0.55 and 0.50– 0.60 respectively. [13]

When included in the regression, capacity utilization comes in with a positive and significant coefficient as expected, but almost without bringing about any changes in the other estimated parameters (compare the first and second columns of each panel of Table 2). Interestingly, the estimated coefficient of capacity utilization is in levels about equal to that of capital, and in first differences it does not fall for the French sample, and decreases much less than that of capital for the Spanish sample. The likely reason is, of course, in the role that this variable plays in the adjustment of the capital stock in place in the firm to the unanticipated (or anticipated as transitory) variations of its production.[14]

Using undeflated value added or deflating it by an industry price index or by an individual firm price index has almost no consequence on the estimates (compare the second, third and fourth columns of each panel of Table 2). We should just conclude that, as far as the conventional OLS panel data estimators are relevant and we are focusing in estimating the elasticities of interest, it does not make a difference whether we consider the revenue function or the production function. The inclusion of the industry and firm price indices as right-side variables does not make more of a difference

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[13] While the first -difference transformation of the data takes care of the biases arising from correlated firm effects, it is well known, however, that this transformation exacerbates the importance of the downward biases arising from errors in variables. This is a likely explanation for the large downfall in the production function estimates of the elasticities of capital, labor and scale in first differences. See for example, Mairesse (1990) and Griliches and Mairesse (1998).

[14] To put it differently the capital stock, as we measured it on the basis of the firm book value in the balance sheet, is a better proxy of the capital services if adjusted by the changes in capacity utilization. Using, when possible, such an adjusted measure in the production function may be to a large extent more appropriate and can do much to limit the sharp downfall in the estimates of capital elasticity in first differences as compared the estimates in levels.

in the other parameter estimates (compare columns 5 and 6 to the previous ones). Their own coefficients, however, both in the levels and first differences regressions, tend to be significant, positive and not too different for the French sample, but surprisingly of different signs for the Spanish sample. This is hardly interpretable, because both price indices cannot be viewed only as missing deflators, but also as variables which are likely to be correlated with the error term, both because of likely errors in variables and the endogeneity of output prices (through the firm demand equation).[15]

3.4 IV panel data estimates.

Tables 3 to 5 display the results of applying a number of IV or GMM panel data estimators.[16] Let us briefly review what these estimators are, before presenting their results. Firstly, keeping the production function equation specified in levels we instrument the endogenous capital and labor variables with their past differences or with the differences of the external instruments (estimates presented in the upper panels in Table 3 and in Table 5).[17] The external instruments which we employ to instrument the capital and labor variables are the firm-specific average wage and a firm-specific index of the price paid by intermediate consumption (materials, energy and services). Secondly, writing the production function equation equations in first differences to remove the firm individual effects, we instrument the endogenous capital and labor variables with their

[15] We have also carried out "within firm" and "long differences" panel data estimates, which can be found in the working version of the paper. "Within firm" estimator refers to OLS performed on the deviations of the variables to their firm means, and "long differences" estimator refers here to OLS performed on the four year lagged differences of the variables. While these estimators tend to produce estimates somewhere in between to the estimates in levels and first differences estimates, our conclusions are basically unchanged.

[16] The precision of the IV estimates for the French sample suffering much from its very short period (four years), we present only for it the results of Table 3. The estimates for the Spanish sample were also extremely imprecise when we reduced it for comparison sake to a balanced sample over four years.

[17] Such estimators have been strongly advocated, for example, in Arellano and Bover (1995).

past levels (lower panels in Table 3).[18] In both cases, we convinced ourselves that it was more appropriate to consider that the capacity utilization and output price variables (when included in the production function specification) were only contemporaneously correlated with the disturbance term (resulting from errors in measurement among other reasons). Consequently, we instrument them using both past and forward values of their levels or differences. In any case, using simply the lagged values as instruments did not resulted in any noteworthy changes, only less precise estimates. Finally, we also experiment with the production function equation specified in quasi-differenced form, which allow for a possibly first-order serially correlated disturbance v_{it} in the original equation, using as instrument the endogenous capital and labor variables with their past differences[19]. Table 4 presents these estimates; the upper panel shows the unconstrained estimates, from which we compute the minimum distance estimates of the underlying parameters, while the lower panel gives these estimates and reports on the chi-square test (or COMFAC test) of the imposed constraints.[20]

The IV estimates of the elasticity of capital tend to be generally higher than the OLS estimates in first differences. Again, however, they tend to vary more with the estimation procedure than with the particular specification of the production function equations. The highest and most significant estimates are in fact obtained when the

[18] See for example Arellano and Bond (1991).
[19] See Blundell and Bond (2000), who also apply this type of estimator to the estimation of the production function. We have also estimated other variants of this estimator with similar results or worse.
[20] All the IV estimators reported here are set in a GMM framework, using (part of) the available moment restrictions at each cross-section. We always constrain the number of instruments, using the closest a priori legitimate lags or leads. The instruments in each case are detailed in the footnotes of the Tables. All estimates reported are first-step estimates, based on the first-step estimator of the weighting matrix based on the variance-covariance matrix of the instruments. The reported standard errors are robust to heteroskedasticity across firms and arbitrary time correlation. For all specifications we report the Sargan test of overidentifying restrictions. For the specifications in first differences, we also report the test of first and second order auto-correlation of the residual proposed by Arellano and Bond (1991).

equations in levels are instrumented with lagged differences of the variables, and also, in the case of the Spanish sample, when using external (differenced) instruments, and when instrumenting the levels of the quasi-differenced equations. On the other hand, the IV estimates on the first differenced equations are extremely imprecise (and practically worthless) in the case of the French sample, and still quite poor, although much less for the Spanish sample. The problems generated by differencing the equations are actually aggravated by the fact we use only the lagged variables as instruments and by the relatively small size of our samples.[21].

In contrast also to the OLS estimates in first differences, the hypothesis of constant returns to scale is accepted by all the IV estimates. The best estimates here are, once more, obtained for the Spanish sample when the production function equations in levels are instrumented by the lagged differences of the variables (and the external instruments also): the relevant scale parameter (μ-1) is very close to zero, and relatively precisely estimated. The other estimates, however, are more imprecise even when instrumenting the equations in levels, and again they appear quite poor when instrumenting the equations in first differences.

The coefficient on the capacity utilization variable tends to vary widely, even more so than the elasticity of capital, and in way mainly related to the method of estimation. It can be noted that this variable turns out to be crucial to obtain at least sensible looking, though still imprecise, estimates when instrumenting the equations in

[21] The "poor" performances of these first differenced IV (or GMM) estimators in such cases are neither new nor very surprising. See for example the simulations by Crépon and Mairesse (1995) for a sample of comparable size to the French sample (T=3 and N=400) and a configuration close to that of the estimation of a production function.

first differences for the Spanish sample (lower panel in table 3). It seems clear that at least capacity utilization plays an important role as a control in the production function.

As in the case of the OLS estimates, using undeflated value added or deflating it by an industry price index or by an individual firm price index has almost no consequence on the different IV estimates. Likewise when included as a right-hand variable, output price tends to come in positively and imprecisely, though with a coefficient significantly different from 1. Our IV results just simply confirm our conclusion that it does not make a difference whether we consider the revenue function or the production function. Nonetheless the fact that the output price is coming in positively in the production function but has a negligible impact on the estimated parameters of the other variables indicates that it is positively correlated with the disturbance term. One way to understand this (apparent) puzzle is to view output price as one endogenous determinant among many others of the firm demand function, which should be analyzed in a more general model of firm behavior. This suggests that the ways by which firm output price can indeed be used to improve the identification and estimation of the production function clearly remain to be further investigated, much beyond our simple, yet thorough, present analysis.[22]

4. Concluding remarks.

In their overview of the contribution of panel econometrics to the identification and estimation of production functions, Griliches and Mairesse (1998) emphasize the need to deepen our understanding of firms' behavior and of their sources of heterogeneity, but also the need to improve and enrich the measurement of production

[22] Jaumandreu and Mairesse (2005) is a preliminary paper trying to go some steps in this direction.

and its factors; in particular, they point out how useful it would be to have information on firms' output prices, which is typically lacking. In this exercise, we have explored the impact of incorporating individual firm information on output prices and capacity utilization rates in panel-data estimates of production functions, taking advantage of the availability of such information for two similar samples of French and Spanish firms. Contrary to the conclusions which could be suggested by an *a priori* analysis, we find that, while the availability of information on firms' individual prices directly improves the measurement of production and productivity (and total factor productivity) at the firm level, it does not significantly influence the estimated elasticities of interest of the production function. This holds true whether we rely on the simplest OLS panel data estimators or we use a battery of rather sophisticated IV estimation methods. The same, however, cannot be said for the use of information on capacity utilization rates, which act as an important control, at least in most estimates. In any case, neither type of information can account for the wide disparities which are typically found when contrasting estimates relying mainly on the cross-sectional dimension of the data and on its time-series dimension (say based on the levels of the variables or on their first differences).

These results are in a sense reassuring since they can validate the customary practice of simply deflating output measures (sales, value added,…) by industry output price indices in estimating production functions. Yet, they are also disappointing with respect to the hopes of improving the implausible estimates of capital elasticities and returns to scale that are usually found in the time-series dimension of the data, when one tries to take care of the risks of heterogeneity and endogeneity biases. Our basic conclusion is thus that the failure to account for the dispersion of changes in individual prices probably has much fewer consequences than other specification errors, in particular those linked to errors in variables. Our findings are also somewhat disconcerting to the extent as they seem to imply a great difficulty at distinguishing between the production function and the revenue function, and at estimating a satisfactory firm demand function.

Clearly much remains to be done. Firstly, the results need to be confirmed on different, larger samples, covering longer periods, with price measures based on different information sources, and preferably also for periods, countries, and industries that have experienced significant inflation. Secondly, the estimates suggest that firm output prices and capacity utilization should be given a more explicit role in a model of the firm, trying to take into account that price is a strategic variable in the firm competitive behavior and capacity utilization is an important factor of adjustment to the varying and uncertain condition of demand. This type of modeling can contribute to further improvement in the identification and estimation of production functions. Thirdly, and this is the message on which we want to conclude, more effort should be devoted to develop the measurement of output prices at the firm and product level and to improve the accessibility of these price data for research purposes; it is the only way of opening up a wide field of studies on the behavior of firms and the functioning of markets.

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Table 1: Means, Standard-Deviations and Correlations of the Main Variables in Growth Rates (log first differences)

Panel A : FRANCE	**DLVA**	**DLL**	**DLK**	**DLCU**	**DLPI**	**DLPF**
MEAN (in %)	1.8	0.1	1.6	0.2	0.4	0.3
STANDARD DEVIATION (in %)	18.3	8.6	8.3	6.4	2.5	3.5
CORRELATIONS						
Value added (undeflated) DLVA	1					
Number of employees DLL	0.22***	1				
Physical capital stock DLK	0.05*	0.05*	1			
Degree of capacity utilization DLCU	0.09***	0.04	-0.09***	1		
Industry price DLPI	0.09***	0.08***	-0.05**	0.05*	1	
Firm price DLPF	0.13***	0.10***	0.01	0.07**	0.28***	1

Panel B: SPAIN	**DLVA**	**DLL**	**DLK**	**DLCU**	**DLPI**	**DLPF**
MEAN (in %)	4.2	0.4	5.6	0.5	2.2	1.3
STANDARD DEVIATION (in %)	26.0	12.2	18.4	13.6	3.6	5.2
CORRELATIONS						
Value added (undeflated) DLVA	1					
Number of employees DLL	0.29***	1				
Physical capital stock DLK	0.07***	0.12***	1			
Degree of capacity utilization DLCU	0.09**	0.04**	-0.00	1		
Industry price DLPI	-0.01	-0.04**	0.01	0.01	1	
Firm price DLPF	0.08***	0.02	-0.02	0.05***	0.09***	1

For France: Balanced sample 1995-1997, 468 firms, 1404 observations.
For Spain: Unbalanced sample 1992-1999, 675 firms, 3628 observations.
The stars ***, ** and * indicate that the correlations are statistically significant at a confidence level of 1%, 5% and 10%, respectively.

Table 2: OLS Estimates in Levels and in First-Differences

Panel A : FRANCE	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
LEVELS						
LKL	0.25	0.25	0.26	0.26	0.26	0.26
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LL	0.04	0.03	0.03	0.03	0.03	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LCU	--	0.26	0.25	0.23	0.25	0.25
		(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
LPF (or LPI in regression column 5)	--	--	--	--	0.58	0.23
					(0.26)	(0.14)
R^2 (m.s.e.)	0.998 (0.274)	0.998 (0.274)	0.998 (0.274)	0.998 (0.278)	0.998 (0.274)	0.998 (0.273)
FIRST-DIFFERENCES						
LKL	0.08	0.10	0.11	0.09	0.10	0.09
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
LL	-0.46	-0.45	-0.45	-0.49	-0.45	-0.47
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
LCU	--	0.27	0.26	0.24	0.27	0.25
		(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
LPF (or LPI in regression column 5)	--	--	--	--	0.50	0.56
					(0.22)	(0.15)
R^2 (m.s.e.)	0.074 (0.126)	0.083 (0.126)	0.085 (0.126)	0.087 (0.126)	0.087 (0.126)	0.093 (0.125)

Panel B : SPAIN	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
LEVELS						
LKL	0.22	0.22	0.22	0.24	0.22	0.22
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LL	0.08	0.07	0.07	0.07	0.07	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
LCU	--	0.29	0.29	0.28	0.29	0.29
		(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
LPF (or LPI in regression column 5)	--	--	--	--	-0.26	0.05
					(0.18)	(0.09)
R^2 (m.s.e.)	0.998 (0.379)	0.998 (0.376)	0.998 (0.378)	0.998 (0.395)	0.998 (0.376)	0.998 (0.376)
FIRST-DIFFERENCES						
LKL	0.06	0.06	0.06	0.06	0.06	0.06
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
LL	-0.35	-0.35	-0.35	-0.36	-0.35	-0.36
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LCU	--	0.14	0.14	0.13	0.14	0.14
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LPF (or LPI in regression column 5)	--	--	--	--	-0.27	0.32
					(0.14)	(0.10)
R^2 (m.s.e.)	0.068 (0.175)	0.074 (0.174)	0.051 (0.176)	0.062 (0.176)	0.075 (0.174)	0.078 (0.174)

For France: Balanced sample 468 firms: 1994-97 and 1995-97 (1862 and 1404 observations) for regressions in Levels and in First Differences, respectively. For Spain: Unbalanced sample 675 firms: 1991-99 and 1992-99 (4403 and 3628 observations) for regressions in Levels and in First Differences, respectively.
Standard errors of estimated coefficients, robust to heteroskedasticity across individuals and arbitrary correlation over time are given in parentheses. Year dummy variables are included in all regressions; and industry dummy variables are also included in the regressions in Levels. All variables are in logarithms. LVAL, LVADSL et LVADEL are, respectively, productivity undeflated, deflated by industry price, and deflated by firm price, where productivity is measured in terms of firm value added per employee. LKL is the physical stock of capital per employee at the beginning of the year, measured by the gross book value in the firm balance sheet (adjusted for inflation); LL is the firm's average number of employees; LCU is the firm's degree of capacity utilization; LPI is the industry price variable; and LPF is the firm price variable.

Table 3: IV estimates on levels and on first-differenced equations

Panel A : France	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
LEVELS						
LKL	0.65	0.53	0.54	0.57	0.54	0.53
	(0.25)	(0.22)	(0.22)	(0.23)	(0.23)	(0.18)
LL	0.15	-0.14	-0.14	-0.14	-0.16	-0.13
	(0.21)	(0.15)	(0.16)	(0.17)	(0.16)	(0.14)
LCU	--	1.55	1.51	-1.46	1.51	1.61
		(0.76)	(0.76)	(0.78)	(0.77)	(0.72)
LPF	--	--	--		0.33	0.36
					(0.24)	(0.25)
CHI2(df) / P-value	8.6(4)/0.07	21.9(9)/0.01	20.1(9)/0.02	18.6(9)/0.03	20.4(9)/0.02	26.8(14)/0.02
FIRST-DIFFERENCES						
LKL	0.63	0.53	0.48	0.37	0.45	0.20
	(0.91)	(0.66)	(0.66)	(0.66)	(0.66)	(0.56)
LL	1.28	0.55	0.56	0.56	0.58	0.45
	(0.77)	(0.44)	(0.44)	(0.43)	(0.44)	(0.45)
LCU	--	0.59	0.49	0.46	0.55	0.52
		(0.48)	(0.48)	(0.48)	(0.49)	(0.49)
LPF	--	--	--	--	0.37	-0.10
					(0.20)	(0.29)
CHI2(df) / P-value	3.6 (4)/0.46	19.5(9)/0.02	20.8(9)/0.01	22.2(9)/0.01	20.7(9)/0.01	29.8(14)/0.01
AR1 test	-3.55	-5.88	-6.01	-6.19	-6.07	-6.97
AR2 test	-0.81	-1.01	-0.51	-0.43	-0.81	-0.79

Panel B : SPAIN	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
LEVELS						
LKL	0.28	0.26	0.26	0.27	0.26	0.27
	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.06)
LL	0.10	0.02	0.02	0.02	0.02	0.09
	(0.08)	(0.06)	(0.06)	(0.08)	(0.06)	(0.05)
LCU	--	0.43	0.44	0.48	0.44	0.43
		(0.13)	(0.13)	(0.13)	(0.12)	(0.12)
LPF	--	--	--	-	0.09	0.07
					(0.12)	(0.12)
CHI2(df) / P-value	26.5(24)/0.33	53.6(49)/0.30	55.0(49)/0.26	53.8(49)/0.30	53.6(49)/0.30	80.1(74)/0.29
FIRST-DIFFERENCES						
LKL	-0.06	0.24	0.32	0.33	0.27	0.27
	(0.20)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
LL	-1.01	0.06	0.11	0.14	0.09	0.15
	(0.42)	(0.21)	(0.21)	(0.22)	(0.21)	(0.18)
LCU	--	0.23	0.26	0.23	0.24	0.26
		(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
LPF	--	--	--	--	0.29	0.02
					(0.11)	(0.11)
CHI2(df) / P-value	21.7(24)/0.60	53.9(49)/0.29	56.8(49)/0.21	61.5(49)/0.11	55.9(49)/0.23	73.5(74)/0.50
AR1 test	-5.68	-9.98	-9.74	-9.53	-9.96	-10.02
AR2 test	-1.69	-2.54	-2.30	-2.43	-2.55	-2.47

The samples, notations and definitions of variables are the same as in Table 2. The reported estimates are the first-stage estimates. Standard errors of estimated coefficients are given in parentheses. Year dummy variables are included in all regressions. For instruments in the equations in levels, we use t-1 and t-2 lagged differences of LKL and LL; t-1 and t-2 lagged differences and the t+2 lead difference of LCU; and we take LPF as exogenous in the regression (5) and instrument it by its t-1 and t-2 lagged differences and the t+2 lead difference in regression (6). For instruments in the equations in first differences, we use t-2 and t-3 lagged levels of LKL and LL; t-2 and t-3 lagged levels and the t+1 lead level of LCU; and we take LPF as exogenous in regression (5) and instrument it by its t-2 and t-3 lagged levels and the t+1 lead level in regression (6).

Table4: IV estimates for Spain on quasi-differenced levels equations.

	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
DEPVAR(-1)	0.49	0.50	0.50	0.57	0.51	0.52
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
LKL	0.46	0.40	0.38	0.37	0.40	0.30
	(0.14)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
LKL(-1)	-0.35	-0.27	-0.25	-0.25	-0.27	-0.17
	(0.13)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
LL	-0.12	-0.21	-0.21	-0.19	-0.21	-0.25
	(0.28)	(0.24)	(0.24)	(0.25)	(0.24)	(0.19)
LL(-1)	0.16	0.22	0.22	0.20	0.22	0.29
	(0.28)	(0.24)	(0.24)	(0.24)	(0.23)	(0.19)
LCU	--	0.13	0.13	0.10	0.12	0.14
		(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
LCU(-1)	--	0.02	0.01	0.03	0.02	0.01
		(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
LPF	--	--	--	--	0.20	0.04
					(0.11)	(0.39)
LPF(-1)	--	--	--	--	-0.16	0.02
					(0.12)	(0.40)
CHI2(df) / P-value	32.0(34)/0.57	60.9(58)/0.37	62.3(58)/0.33	58.2(58)/0.47	60.5(58)/0.39	88.7(82)/0.29
ρ	0.48	0.50	0.50	0.57	0.50	0.51
	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.09)
α	0.29	0.31	0.31	0.32	0.32	0.31
	(0.19)	(0.17)	(0.17)	(0.17)	(0.17)	(0.15)
$\mu - 1$	0.06	-0.02	-0.01	-0.02	-0.02	0.05
	(0.42)	(0.36)	(0.36)	(0.38)	(0.36)	(0.29)
δ	--	0.19	0.17	0.14	0.18	0.18
		(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
γ	--	--	--	-	0.16	0.18
					(0.17)	(0.59)
COMFAC / P-value	3.7(2)/0.16	3.1(3)/0.38	2.6(3)/0.46	2.5(3)/0.48	3.3(4)/0.51	4.4(4)/0.36

Unbalanced sample 675 firms: 1992-1999 (3628 observations). The reported estimates are the first-stage estimates. Standard errors of estimated coefficients are given in parentheses. Year dummy variables are included in all regressions. See Table 2 for notation and definition of variables. For instruments we use t-1 and t-2 lagged differences of the dependent variable, and of LKL and LL; t-1 and t-2 lagged differences and t+2 lead difference of LCU; and we take LPF as exogenous in the regression (5) and instrument it by its t-1 and t-2 lagged differences and the t+2 lead difference in regression (6).

Table 5: IV estimates for Spain on level equations using external instruments.

	LVAL (1)	LVAL (2)	LVADIL (3)	LVADFL (4)	LVAL (5)	LVAL (6)
LKL	0.38	0.31	0.30	0.36	0.30	0.31
	(0.10)	(0.09)	(0.09)	(0.10)	(0.09)	(0.07)
LL	0.04	-0.00	-0.00	-0.01	0.01	0.06
	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)	(0.05)
LCU	--	0.48	0.50	0.59	0.50	0.46
		(0.14)	(0.14)	(0.14)	(0.14)	(0.13)
LPF	--	--	--	-	0.12	0.09
					(0.13)	(0.12)
CHI2(dl) / P-value	24.3(24)/0.44	49.8(49)/0.44	51.5(49)/0.38	62.2(49)/0.10	49.5(49)/0.45	76.3(74)/0.40

Unbalanced sample 675 firms: 1991-1999 (4303 observations). The reported estimates are the first-stage estimates. Standard errors of estimated coefficients are given in parentheses. Year dummy variables are included in all regressions. See Table 2 for notation and definition of variables. For external instruments we use t-1 and t-2 lagged differences of LWL and LWM, where LWL is the average firm wage, and LWM is an index of the price of firm intermediate consumption. We also used for instruments t-1 and t-2 lagged differences and the t+2 lead difference of LCU; and we take LPF as exogenous in regression (5) and instrument it by its t-2 and t-3 lagged levels and the t+1 lead level in regression (6).