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How do Firms Respond to Cheaper Computers ? Microeconometric Evidence for France Based on a Production Function Approach

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Microeconometric Evidence for France Based on a Production Function Approach

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Abstract

We implement an original method based on the estimation of a production function, to investigate how the decrease in the cost of computers has affected the marginal cost of firms, their aggregate labor demand and their skill structure. Using a panel of more than 5000 French firms followed between 1994 and 1997, we find that the effects of the decrease in the price of computers have been large both in terms of marginal cost reduction and in terms of skill structure, although these effects exhibit some heterogeneity across firms. In particular, skill substitution effects have been larger in manufacturing industries.

Keywords: labor demand, technological bias, elasticity of substitution.

JEL classification: J21, J23, C33, J31, L60

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I. Introduction

For several decades, firms have benefited from the continuous technical progress achieved by the producers of information technologies, as the data processing power has grown faster than the retail prices of computers. The resulting decline in the cost of computer power may be viewed as exogenously driven by technical innovations[1]. As a result firms have massively invested in computers. In almost all OECD countries, investment in information technologies grew at an average annual rate of 15% during the 90s (Colecchia and Schreyer, 2001). A major concern for researchers has been to measure the global supply shock associated with this accumulation process, as well as the effects on the demand for labor, with a particular focus on the relative demand for skills.

Macroeconomic studies have extensively discussed the magnitude of the supply shock (Oliner and Sichel, 2000; Gordon, 2000). They have also consistently shown that the observed shift in labor demand away from unskilled workers and towards skilled workers, does not originate in the industries most exposed to international trade, thus putting forward the accumulation of computers as the chief explanation. Microeconometric studies on the other hand, have provided evidence of the effect of computer accumulation on the supply of firms (Lehr and Lichtenberg, 1998), on their relative demand for skills (Bresnahan, Brynjolfsson and Hitt, 2002), as well as on the interaction between information technology and work place organization (Brynjolfsson and Hitt, 2000; Caroli and Van Reenen, 2001).

The skill bias issue has usually been investigated in the literature by estimating labor demand equations where the stock of computers is considered as a quasi-fixed input. We argue that it makes more sense to evaluate the impact of the decline in the cost of computers directly, rather than through the accumulation it has generated, if the decline in the cost of computer is the exogenous shock driving the accumulation process. The focus of this paper is thus deliberately on the effects of the decline in the price of computers.

The strong decline in the price of computers may be viewed as exogenous inasmuch as it is the result of technological innovations that have occurred in a circumscribed set of IT-producing industries. Nonetheless, Acemoglu (1998) argues that these innovations have actually been spurred by an upwards shock on the relative supply of skill, enlarging the benefits of research and developments in technologies complementary with skilled labor. If this story is true, the decline in the price of computers is to some extent endogenous. However, this discussion lies upstream from our study since the decline in the price of computers can still be considered exogenous at the firm level, whatever the nature of the truly exogenous macroeconomic shock.

Focusing on the price decline experienced by computers is thus fine in principle, yet proves tricky in practice, as the evolution of the purchase price of computers is identical for every firm at a given date. No direct identification of the impact of this exogenous shock is therefore possible from the estimation of factor demand equations. We develop an original methodology based on the primal approach to circumvent this limitation. We show that it is possible to measure computer price effects on both the marginal cost and the labor demand of firms, solely by estimating a production function.

We take advantage of the fact that, given a technology and a level of output, the relative prices of inputs locally determine unique levels of inputs under the assumption of cost minimization. Therefore, the elasticities of factor demands to the prices of inputs can be expressed as functions of the technology and the levels of inputs, without any additional information on factor costs being required. We derive such relationships for the elasticities of aggregate labor demand as well as its composition by skill, to the price of computers. In order to provide an assessment of the associated supply shock, we also derive the analog expression for the marginal cost of production.

Implementing this strategy obviously requires assumptions on the functional form of the production function, whose estimate enters the computation of the parameters of interest. We estimate a translog production function, which is flexible enough to account for a wide variety of substitution patterns across firms. The corresponding identifying restriction consists in assuming the constancy across time and a given subsample of firms used for estimation, of the first and second order coefficients of the translog (i.e. the homogeneity of the technology across the firms involved in the estimation).

Whether the production function framework is best suited for the purpose of modeling the changes induced by computerization is subject to discussion. Athey and Stern (1995) suggest for instance an *organizational design production function* which takes into account the fact that organizational design practices may affect output by switching from one production function to another. Such a framework may be more appropriate since computers are said to affect the adoption of organizational design practices by lowering their cost. In this framework, our translog production function must be thought of as the best approximation available.

Our approach allows to evaluate firm-specific effects of the decrease in the price of computers, as our measures of these effects depend on the level of inputs, which may differ across firms due to factor cost heterogeneity. This method thus yields a distribution across firms of the quantitative effects of a fall in the price of computers on the marginal cost of production, as well as on labor demand and the relative demand for skills.

Data limitations have frequently been an important shortcoming in studying the effect of computer accumulation. Studies usually have at their disposal a small sample of firms followed for only one year. By contrast, our evaluations are performed using a very large panel of firms (more than 5000) followed over the period 1994-1997. This data set results from the merging of various sources of information which provide us with a quantitative measure of the stock of computers within the firm, as well as the structure by skill of its workforce and the corresponding wages.

Our measure of the computer stock corresponds to the "Office, Computing and Accounting Machinery (OCAM)" item of the balance sheet of firms. Our measures of employment and wage by skill within the firm, originate in a large amount of work performed at INSEE, which has consisted in aggregating at the firm level exhaustive social security employee level files providing information on skill as well as labor cost.

Our results point to a significant impact of computerization on the marginal cost of production, labor demand and the relative demand for skills. The decrease in the cost of computer has induced a significant decrease in the marginal cost of production. It has also shifted the relative demand of labor toward skilled workers at the cost of unskilled.

The remainder of the paper is organized as follows. In the first section, we define a set of parameters of interest relevant for assessing the impact of the fall in the price of computers on the marginal cost of production, the demand for labor and the skill structure. We derive their expression as functions of the technology and the levels of inputs. The data are presented in the second section together with our estimates of the Translog technology of production. The third and last section is devoted to the computation of the firm-specific parameters of interest, using the production function estimates obtained in the second section. We discuss their significance when compared to aggregate evolutions.

II. Measuring the economic effects of a decrease in the price of computers

We define a set of parameters measuring the effect of a fall in the price of computers on the marginal cost, the demand for aggregate labor and the relative demand for skills by the firm. We then show how to compute them from the technology of production.

Defining the parameters of interest

Consider a production function $y = f\left(x_u, x_s, x_c, x_o\right)$, where x_u and x_s denote unskilled and skilled labor, x_c is the stock of computers, and x_o is the stock of the capital goods other than computers. The cost function associated with this technology is defined by :

$$C\left(p_u, p_s, p_c, p_o, y\right) = \min_{\{x_u, x_s, x_c, x_o\}} \left(p_u x_u + p_s x_s + p_c x_c + p_o x_o\right) \quad s.t. \quad y = f\left(x_u, x_s, x_c, x_o\right)$$

Denote x^* the solution to the above program, conditional on the level of output y^* and the initial vector of factor costs $p^* = \{p_u^*, p_s^*, p_c^*, p_o^*\}$. Assume that factor demands are initially equal to x^*, and consider an exogenous shock driving down the cost of computers. We want to assess the effects of this shock on the new vector x of factor demands, conditional on the technology f and the initial vector of inputs x^*. Table 1 defines our three parameters of interest: the one related to the effect on the marginal cost $\chi_c\left(f, x^*\right)$ and the two related to labor demand $\eta_{lc}\left(f, x^*\right)$ and $\psi_c\left(f, x^*\right)$.

All these parameters are defined "all other input prices and output held constant", and evaluated around the state defined by the initial level of factor demands. Notice that if initial factor prices (therefore initial states) differ across firms, the parameters of interest are also firm-specific.

The first parameter χ_c is a measure of the supply shock associated with the reduction in the price of computers. The decrease in the cost of a particular input affects the marginal cost of the firm, which in turn induces – for a given market structure – a variation in the production price and the demand addressed to the firm[2].

The parameter χ_c enables us to compute a contribution of the decrease in the price of computers to the reduction in the marginal cost, simply equal to $\chi_c \Delta \ln p_c$. We assume that all firms face the same change $\Delta \ln p_c$ in the cost of computers[3]. The contribution to the reduction in marginal cost is nevertheless firm-specific since the parameter χ_c depends on the initial level of inputs which is heterogeneous across firms. $\chi_c \Delta \ln p_c$ thus provides an assessment of the supply shock associated with computerization, different from the one defined in the standard growth accounting framework[4].

The last two parameters η_{lc} and ψ_c summarize the effects on the demand for labor inputs, which result from substitution effects taking place between all four inputs, conditional on a given level of output.

As shown by Fuss and McFadden (1978), all above parameters can be expressed in the primal approach.

Computing the parameters of interest as a function of technology and the initial state

Let us first define the **elasticities of marginal cost to prices** χ_i and to output δ_y:

$$d\ln C_y = \sum_i \chi_i d\ln p_i + \delta_y d\ln y$$

χ_i and δ_y may be expressed as functions of the first and second derivatives of the production function f, for a given level of inputs (see appendix 1):

$$\begin{aligned} \chi_i &= f_i F_i / F \\ \delta_y &= f F_0 / F \end{aligned} \qquad [1]$$

where F is the determinant of the bordered Hessian[5], and F_0 and F_i are the co-factors of respectively 0 and f_i in F.

The intuition behind the expression of χ_c is not straightforward in the general case. However, in the special case of homogeneity of the production function, the following simple relation holds between the elasticity of production to computers $\varepsilon_c = x_c f_c / f$ and the elasticity of scale $\theta = \varepsilon_c + \varepsilon_o + \varepsilon_u + \varepsilon_s$:

$$\chi_c = \varepsilon_c / \theta$$

In order to examine the **effect on labor demand of a decrease in the price of computers**, let us consider the compensated demand for inputs. It involves the price elasticities η_{ij} of factor *i* to factor price p_j and the elasticities to output μ_{iy}:

$$d\ln x_i = \sum_j \eta_{ij} d\ln p_j + \mu_{iy} d\ln y \qquad [2]$$

Again, these elasticities can be expressed in the primal approach as functions of the bordered Hessian F and its co-factors, for a given level of inputs (see appendix 1):

$$\begin{aligned} \eta_{ij} &= \varepsilon_j \sigma_{ij}^{A} / \theta \\ \mu_{iy} &= (f / x_i)(F_i / F) \end{aligned} \qquad [3]$$

where $\sigma^A_{ij} = \left(\sum_k x_k f_k \Big/ x_i x_j \right) \left(F_{ij} / F \right)$ [4] are the Allen-Uzawa partial elasticities of substitution (AUES) and F_{ij} are the co-factors of f_{ij} in F.

The sensitivity of the aggregate labor demand and relative demand for skills can be expressed simply as linear combinations of the two price elasticities η_{uc} and η_{sc}.

The elasticity of aggregate labor to the price of computers is simply a weighted sum of these two elasticities:

$$\eta_{lc} = \frac{x_u}{x_u + x_s} \eta_{uc} + \frac{x_s}{x_u + x_s} \eta_{sc} \qquad [5]$$

The sensitivity of the relative demand for skills is obtained by subtracting the equations of compensated demand (equation [2]) for the two labor inputs. It is thus simply defined[6] as :

$$\psi_c = \eta_{sc} - \eta_{uc} \qquad [6]$$

The fall in the price of computers is said to be biased toward skilled labor when $\psi_c < 0$, in other words when the Allen-Uzawa elasticity of substitution between unskilled labor and computers is larger than that between skilled labor and computers.

Notice that the relative demand for skills can be expressed as

$$d \ln \left(x_s / x_u \right) = \sigma^{\mathrm{M}}_{us} d \ln p_u - \sigma^{\mathrm{M}}_{su} d \ln p_s + \psi_c d \ln p_c + \psi_o d \ln p_o + \left(\mu_{sy} - \mu_{uy} \right) d \ln y \qquad [7]$$

where $\sigma^{\mathrm{M}}_{ij} = \varepsilon_j \left(\sigma^A_{ij} - \sigma^A_{ii} \right) \Big/ \theta$ are the *Morishima elasticities of substitution* (MES).[7]

Another interesting parameter is the ratio $-\psi_c / \sigma^{\mathrm{M}}_{us}$. According to equation [7], it represents the reduction in unskilled labor cost required in order to compensate a 1% decrease in the computer price.

In the following section, we present the data and estimate the technology of production $\hat{f}$, first assumed to be homogenous across all firms of our sample, then across two subsamples corresponding respectively to the manufacturing and non manufacturing industries. In the last section, we use these production function estimates as well as the expressions given in this section, to compute the firm-specific parameters of interest $\chi_c\left(\hat{f},x^*\right)$, $\eta_{lc}\left(\hat{f},x^*\right)$, $\psi_c\left(\hat{f},x^*\right)$. Appendix 2 contains the expressions of the main parameters defined in this section under the translog specification, which we adopt in our empirical work.

III. Data and estimation of the technology of production

The data

The dataset we use is obtained by merging two different sources, the Bénéfices Réels Normaux (BRN), an employer-level file, and the Déclarations Annuelles des Données Sociales (DADS), an employee-level file. It covers the period 1994-1997 and includes 5 255 continuing firms.

The BRN consists of firms' balance sheets and is collected by the Direction Générale des Impôts. It provides us with all the information needed to estimate production functions : employment, capital stocks, value-added, as well as total wages. This file includes around 600,000 firms in the private non financial non agricultural sectors each year and covers around 80% of sales. Firms are identified through a specific code SIREN that allows to follow firms over time. Capital stocks are constructed using information on fixed assets. In particular the item "Office, Computing and Accounting Machinery" (OCAM) is used as a measure of the computer stock. Information distinguishing the OCAM item from the other fixed assets are nevertheless not available for all firms submitted to the BRN regime. We have limited our study to the balanced sample of around 10,000 firms where this information is available over the period 1994-1997.

The OCAM item only provides a raw measure of the stock of computers stricto sensu, as it also contains office equipment (such as typewriters, telephone handsets), as well as furniture (desks, chairs) . We correct for this by taking only a fraction of the OCAM item in measuring the stock of computer capital. This fraction has been set at 50% on the basis of national accounts data[8]. This correction is not an important one when estimating the model. However it has an important effect when measuring the share of computer in total cost. This share, a key parameter in the growth accounting framework, plays also for us the role of a benchmark to which we will compare our measure of the elasticity of production to computer.

A second issue arises from the fact that fixed assets are valued in company accounts at the historic (acquisition) cost, whereas we need a measure of the volume of fixed assets at the replacement cost. In order to recover a capital stock in volume, we have performed a correction which consists in deflating the initial measure by the investment price index at the date considered, minus an estimated age of capital. This amounts to assuming that all the capital was accumulated through a lumpy investment. The age of capital is calculated from the ratio of depreciated asset to asset stock and multiplied by an assumed duration of service life of 5 years. The price index for computer investment is the one compiled by INSEE according to the hedonic method. Quality improvements are therefore taken into account in computing the volume of computer stock.

The correction from historic to replacement cost has also been used for the six other types of capital goods available in tax returns (construction, buildings, general and technical installations, transport equipment, reusable packaging). These capital goods are then aggregated into a single Divisia index. The real value added is defined as the difference between production and materials divided by the value added price index at the two digit level available from national accounts.

We performed some elementary cleaning over the ratios of inputs to value added. We imposed that their mean and standard error belong to the interval built from the median ±5 times the difference between the upper and lower quartiles. The file at this stage has around 8 000 firms over the period 1994-1997.

The DADS is an exhaustive dataset available since 1994[9], containing information about all employees of all firms. The data source consists in mandatory employer reports of the gross earnings of each employee subject to French payroll taxes. This file includes around 15 millions workers per year. Note that workers can only be followed for two adjacent years. We have at our disposal files covering all successive couples of years between 1994 and 1997 : 1993-1994, 1994-1995, 1995-1996 and 1996-1997. The identifying code of workers changes from one file to the other. The files provide information on working days, working hours, wages and various characteristics of the employee (sex, age, occupation) for all firms in the private sector. It also includes the identifying code of the firm SIREN. Labor costs were first computed from wages by applying the payroll taxes rule (this complex rule has changed during the covered period, especially through the introduction of a reduction in payroll taxes for low wage workers). Employee level information was then aggregated at the firm level into two broad categories of occupations : office and manual workers (unskilled labor hereafter) are opposed to business heads, senior executives and intermediate occupations (skilled labor hereafter). For each category, the number of days and hours worked as well as the labor costs are available. Note that unskilled labor represents more than 50% of total labor so that our definition of unskilled does not only cover the population of low wage workers (see Figure 1).

The two files were merged using the identifying code SIREN for the year 1994 to 1997. The quality of the match is not perfect. The reason for this remains unclear up to now. This reduced the size of the data set to a balanced sample of 5112 firms over the period 1994-1997. It covers all sectors of manufacturing and services. Table 2 displays some simple descriptive statistics.

Estimation of the production function

We estimate a production function specified as a Translog function, that is for firm *n* at period *t*:

$$\ln y_{nt} = \alpha_0 + \sum_i \alpha_i \ln x_{int} + \frac{1}{2}\sum_{ij} \beta_{ij} \ln x_{int} \ln x_{jnt} + u_n + u_{nt} \text{ with } \beta_{ij} = \beta_{ji}$$

This specification is general enough in the sense that it is a second order approximation to any technology of production. It has the desirable property that AUES are allowed to differ from unity and to be heterogeneous across inputs. The derivatives of this production function with respect to the levels of inputs, which are needed for the computation of the parameters of interest, are simple functions of the $\{\alpha_i, \beta_{ij}\}$ and the levels of inputs.

The estimation of production functions has been the focus of a large amount of econometric work, because of the strong biases involved when the estimation is carried out using simple OLS. Griliches and Mairesse (1995) (GM) explain the nature of these biases at length. Apart from measurement errors and omitted variables, the main source of bias is the existence of simultaneity between unobserved terms and the quantities of inputs : some shocks either permanent or transitory experienced by firms are taken into account while deciding on the levels of inputs to be used. Part of the unobserved term is thus *transmitted* to inputs in the GM terminology. The induced correlation between the error term of the production function and the explanatory variables, leads to biased OLS estimates.

Permanent shocks correspond to fixed effects u_n appearing in the technology of production : estimations carried out in the within dimension or in differences are unbiased. When transitory shocks occur, however, the within and difference transformations no longer protect against biased estimates. The traditional way of dealing with this problem is the use of instrumental variables in the GMM setting.

More precisely, writing the specification of the production function as

$$y_{nt} = x_{nt}b + u_n + u_{nt}$$

the basic GMM estimator proposed by Arellano and Bond (1991) is based on the identifying restrictions :

H1: $E\left(u_{nt}x_{ns}\right) = 0 \quad s < t$

which lead to the well known set of orthogonality conditions :

S1: $E\left(\Delta u_{nt}x_{ns} = 0\right) \quad s < t-1$

The restriction of no serial correlation in the time varying perturbations may be imposed further :

H2: $E\left(u_{nt}u_{ns}\right) = 0 \quad t \neq s$

Under this assumption, the following orthogonality condition may be used for estimation in addition to S1 :

S2: $E\left(\Delta u_{nt}y_{ns} = 0\right) \quad s < t-1$.

In other words, moment conditions involving lagged values of the endogenous variable may be added to the set of moment conditions based on lagged regressors. However, the classical Arellano and Bond estimator, where lagged levels are used to instrument a first-differenced model, usually performs poorly as instruments are only weakly correlated with explanatory variables. An alternative specification is the Arellano and Bover (1995) estimator, based on the additional assumption that the correlation between the fixed effect and the explanatory variables is constant over time:

H3: $E\left(u_n x_{ns}\right) = \delta$

Under this stationarity assumption, the following orthogonality conditions hold :

S3: $E\left(\left(u_n + u_{nT}\right)\Delta x_{ns}\right) = 0 \;\; s < T$,

as well as

S4: $E\left(\left(u_n + u_{nT}\right)\Delta y_{ns}\right) = 0 \;\; s < T$

under assumption H2.

Estimators based on the sets of moment conditions S1 to S3 or S1 to S4 are known as System estimators. As usual in GMM estimation, a test of the consistency of the extended set with the set S1 is provided by a Sargan test of overidentification.

Blundell and Bond (1998) deals with the case of a time varying perturbation exhibiting autocorrelation, modeled as a simple AR(1) process :

$$u_{nt} = \rho u_{nt-1} + \varepsilon_{nt} .$$

The quasi-differenced model can be written as:

$$y_{nt} = \rho y_{nt-1} + b\left(x_{nt} - \rho x_{nt-1}\right) + \left(1-\rho\right)u_n + \varepsilon_{nt}$$

Blundell and Bond (1998) shows that the assumptions H1 to H4 can be extended to the quasi-differenced model and lead to a set of orthogonality conditions S1 to S4 in which u_{nt} is replaced by ε_{nt}. Notice that the validity of the orthogonality conditions set S4 (based on lagged values of Δy) requires the additional assumption that the process generating the data started a long time before the first observation of the data, so that the correlation between the instrument and the fixed effect can be neglected.

Two specific estimation problems must be addressed in order to estimate the technical coefficients α_i and β_{ij} consistently. The first problem is the presence of measurement errors, the second is non linearity. Both are connected.

Our measurement of the computer stock is particularly likely to be affected by large errors since it is based on the item OCAM, as explained in the data section. Computers stricto sensu are only one part of this item, so that the true stock of computers one would wish to have access to is : $K_{nt}^{*} = \Theta_{nt} OCAM_{nt} = \Theta_{nt} / \Theta \, K_{nt}$, where Θ_{nt} is the individual share of computer stock in the OCAM item, Θ the average share used for all firms (here 50%) and K_{nt} the measure of the computer stock we have used. In logarithms one obtains $k_{nt}^{*} = k_{nt} + \theta_{nt}$ where $\theta_{nt} = \log\left(\Theta_{nt} / \Theta\right)$. The shares may exhibit persistent heterogeneity across individuals. Let us model these shares, as a first approximation, as $\theta_{nt} = \theta_{n} + \eta_{nt}$, and assume away serial correlation in the η_{nt} terms. These assumptions are sufficient to deal with the measurement issue properly using GMM in the case of a linear specification like a Cobb-Douglas production function, as the firm-specific terms θ_{n} always drop off either in instruments or in the differenced equation itself, and the assumption of no serial correlation of the remaining term insures that the estimators will be consistent. Similarly, the within or long difference estimators eliminate the firm specific component, which leaves either $\left(\eta_{nt} - \eta_{n.}\right)$ or $\Delta\eta_{nt}$ as the only part of the perturbation linked to the measurement issue.

The second estimation issue is non linearity. Crossed terms are difficult to estimate, especially in the presence of measurement errors for which no simple instrumental variable strategy is available (Hausman, Newey and Powell, 1995; Hausman, 2001). To see this consider the following simple model:

$$y_n = \gamma \; x_n^{*2} + u_n$$

Assume the standard measurement model:

$$x_n = x_n^{*} + e_n$$

The model based on the observable variables is then written :

$$y_n = \gamma \ x_n^2 + u_n - 2\gamma \ e_n x_n^* - \gamma \ e_n^2$$

An instrumental variable for the measurement error problem is usually a variable correlated with the true measure but independent of the measurement error. It is this way at least that GMM estimation solves the measurement error problem, assuming these errors not correlated through time (Griliches and Hausman, 1986). In this case such an instrument would not be suitable, since :

$$E\left(u_n - 2\gamma \ e_n x_n^* - \gamma \ e_n^2 \middle| z_n\right) = -\gamma \ E\left(e_n^2 \middle| z_n\right) = -\gamma \ E\left(e_n^2\right) \neq 0$$

Even standard GMM panel estimator would not be consistent. Reducing this bias requires a procedure that insures that the variance of the measurement error is small[10]. As the firm-specific component of the residual variance encountered in microeconometric studies is usually the most important, an appropriate procedure should not be a specification involving the equation in levels, such as the Blundell and Bond estimator. Using within or long difference estimators is one way to reduce this bias, as such estimators remove the permanent component in the residuals due to measurement errors and its square. The Arellano and Bond estimator has the same desirable property, as well as that of correcting for simultaneity and measurement error biases. However, we show that it yields imprecise estimates, probably due to the weak instruments issue.

Turning to the estimation, we present traditional methods dealing with the correlated effect (within and long differences) as well as two nonlinear GMM estimators based on the quasi differentiated model of Blundell and Bond (1998). The first GMM estimator relies on the sets of orthogonality conditions S1 and S2 based on the quasi-differentiated model (hereafter GMMDIFQD). The second GMM estimator is the corresponding system estimator (hereafter GMMSYSQD). We also present the between estimator as a benchmark.

We measure the volume of labor by the number of days worked, using the number hours worked per day as an additional control variable, possibly interacted with other inputs. Ignoring the latter variable would induce to an omitted variable bias since the elasticity of production with respect to days may differ from the elasticity to hours. The number of hours per day is also likely to adjust more quickly than the other regressors and thus capture simultaneity biases.

All inputs have been centered at the mean of the sample before computing cross-products so that first order coefficients can be interpreted as average elasticities.

Table 3a displays the estimation results using the whole sample for the within estimator, the long difference estimator, the two GMM estimators and finally the between estimator. Separate estimations are then carried out for the manufacturing and non manufacturing industries, as shown in table 3b (within, GMMDIFQD and GMMSYSQD).

Table 3a shows strong differences in first order coefficients across estimators. The average elasticity of production to computer is very high (around 0.15) for estimators that involve levels, namely between and GMMSYSQD. The average elasticity is much lower with GMMDIFQD, within and long differences that abstract from levels. The average elasticity for the within and long difference estimators are very close, around 0.03, and significantly different from zero. GMMDIFQD yields a negative but strongly imprecise average elasticity. This result is clearly not in favor of the “level” estimations. Indeed, as will be further discussed later, one puzzle associated with the estimation of production functions involving computer stocks is the existence of excess returns to computers compared to their share in total cost (which is usually evaluated around a few percents). From this point of view, within and long difference perform better than between and GMMSYSQD that lead to average elasticity too large to be consistent with plausible orders of magnitude.

Estimates of the elasticity of scale are very close for all estimators except GMMDIFQD (that yields a dubious value of 1.46), ranging from 0.88 to 0.98. Notice that using the numbers of hours worked per day (by category of workers) as additional controls has little effect on the estimated parameters. The elasticity of scale however tends to be higher : the within estimator obtained by omitting these controls leads to an average elasticity of scale of 0.80 (unreported regressions).[11]

Table 3b displays the analog results based on two subsamples restricted to the manufacturing and the non manufacturing industries respectively. The picture is quite similar to the one obtained from the pooled estimation. The within estimate of the elasticity to computers averages the consistent value of 0.03 for both manufacturing and non manufacturing industries, while it is much higher for GMMSYSQD (0.09 and 0.19 respectively).

The second order coefficients usually exhibit the same pattern across estimators but with some noticeable exceptions. We mainly look at crossed terms involving computers. The crossed term *unskilled workers*computer stock* is usually negative, only significantly so for the between and within estimators. GMMSYSQD yields a positive but insignificant value. This negative crossed effect is obtained at the industry level for all estimators. It is significantly negative in the manufacturing industry.

By contrast, the crossed term *skilled worker*computer stock* is generally positive. It is only negative with GMMSYSQD and not significantly so in the industry regressions (table 3b). Focusing on the within estimator, the crossed term is significantly positive in the pooled estimation (table 3a) and in the manufacturing industry.

Our conclusion at this stage is that within and long difference estimators yield the most convincing estimations. Of course within and long difference do not solve all the problems associated with the production function estimation. However the GMMSYSQD does not solve all problems either as shown above because of the measurement errors and the non linearity of the Translog production function. Besides, it does not pass the Sargan specification test and leads to unreasonably high elasticities of production to computers. GMMDIFQD, which is a priori more reliable but subject to the weak instruments issue, gives very imprecise results. Furthermore, the additional control variables we have introduced (hours worked per day) can capture and reduce the simultaneity bias in the within and long difference estimations. In the rest of the paper, we therefore work with the traditional within estimation.[12]

The features of the estimated technology of production are further discussed in the next section by looking at the parameters of interest defined in the first section.

IV. Assessing empirically the effects of a decrease in the price of computers

Recall from the first section that the parameters of interest $\chi_c\left(\hat{f},\bar{x}\right)$, $\eta_{lc}\left(\hat{f},\bar{x}\right)$, and $\psi_c\left(\hat{f},\bar{x}\right)$ are fully defined by the parameters $\left\{\alpha_i,\beta_{ij}\right\}$ and the initial level of inputs x^*. It is therefore possible to compute them from one of the previously estimated production function $\hat{f}=\left\{\hat{\alpha}_i,\hat{\beta}_{ij}\right\}$, conditional on some initial level of inputs x^*. As argued in the previous section, we favor here the within estimator. Besides, a natural choice for the level of inputs is the individual average of factor levels over time $\bar{x}$. Since the average factor levels differ across firms, these parameters are firm specific.

We consider successively the effect on the marginal cost (parameter χ_c) and on labor demand (parameters η_{lc} and ψ_c). We first display the values of the parameters of interest computed on the basis of the production function estimation carried out using the whole sample of 5112 firms, i.e. assuming the homogeneity of the technology across the whole economy. We comment on the macroeconomic significance of these results. Recall however that the production function estimates carried out separately on manufacturing and non manufacturing industries, differ somewhat as far as the magnitude and statistical significance of the second order coefficients involving computer capital are concerned. We thus comment on the robustness of the previous results when manufacturing and non manufacturing industries are considered separately.

Effect on the marginal cost

We find the supply shock associated with the decrease in the price of computers to be large and quite heterogeneous across the sample. Table 4 displays the 25%, 50% and 75% fractiles of the distribution of χ_c. The median value is 0.05 : all other input prices and output being held constant, a decrease in the price of computer by 15% (about the average annual change in the French hedonic price over the period 1990-1999) should induce a decrease in the marginal cost of the median firm by 0.75%. This represents a substantial contribution, given that the price of value-added has actually decreased by 1.4% a year relatively to the average labor cost between 1990 and 1999. The effect of the decline in computer cost is sizeable even at the bottom of the distribution : the first quartile of the parameter is equal to 0.04, which corresponds to a marginal cost decrease by about 0.6%.

Another way of assessing the extent of the supply shock is to compare χ_c to the ratio ε_c/θ of the elasticity of production to computers divided by the elasticity of scale, and to the share π_c of the remuneration of computers in total cost. Recall that under the assumption of homogenous production function of degree θ, χ_c should be equal to ε_c/θ. Besides, if firms are price-takers on the inputs markets and optimize correctly, ε_c/θ must equal the share π_c. Table 4 however shows the former to be much larger than the latter. This result is supported by recent studies (Lehr and Lichtenberg, 1998; Stolarick, 1999; Brynjolfsson and Hitt, 2000). It may point to excess returns of computers and thus under investment. An alternative explanation is that the effect of computers captures something larger than returns to computers stricto sensu, as the stock of computer capital is bound to be correlated with unobserved complementary inputs such as software or with complementary workplace organization processes. In this case, the price elasticities we commented on are elasticities not to the computer price but to the price of an aggregate of all the inputs for which computers serve as a proxy.

Effects on labor demand

We analyze here the effect of the computer price decrease on the structure of the demand of firms with a particular focus on the two labor inputs. Table 5 presents the AUES that sum up to some extent the pattern of substitutability of the estimated technology. However, we comment directly on computer price elasticities (see their sample quartiles in table 6) rather than the corresponding AUES.[14]

The primary effect of a decrease in the price of computers is an accumulation of computer capital whose magnitude depends on its degree of substitutability with other inputs. We find that the three quartiles of its own price elasticity are not significantly different from -1, which means that, apart from volume effects, a decrease in computer prices should lead to an increase in computer stocks by roughly the same proportion. Notice that with a Cobb-Douglas specification the price elasticity would have been $-\left(1-\varepsilon_c/\theta\right)$ which is close to –1 given the small magnitude of the elasticity of production to computer stock. Thus the more flexible pattern of substitutability across inputs implied by the translog production function does not play a major role here. Given that output is held constant, the accumulation of computer capital must be necessarily compensated by a decrease in the use of at least one of the three other inputs. One of the most striking features of our results is that this is only the case for unskilled labor. Indeed, the elasticity of unskilled labor to the price of computers appears to be significantly positive, with a median value of 0.15. By contrast, the estimated quartiles of the price elasticities of skilled labor are negative with a median value of –0.8. The elasticity of the other capital goods is also negative but not significantly so. We can therefore consider that the decrease in the price of computers leads firms to increase the intensity of production in computers and skilled workers, and simultaneously decrease the use of unskilled workers, keeping the stock of other capital goods unchanged.

The effect on aggregate labor demand of a decrease in the price of computers, measured by η_{lc}, involves the two opposite effects on unskilled labor and skilled labor (documented by the price elasticities η_{uc} and η_{sc} in table 6). Table 7 displays the quartiles of the global effect as defined in equation [5]. It has a median value of 0.07 and a 5% confidence interval of [0.03,0.11]. This value is fairly stable across quartiles, ranging from 0.06 to 0.08. Our result can thus be summarized by the statement that computer accumulation is biased towards capital against labor. According to these results, the yearly decline in the computer price by about 15% over the period 1990-1999 has been associated with a negative shift in labor demand for the median firm equal to –1% with a 5% confidence interval of [-1.6%,-0.4%]. Notice that this does not imply that employment decreased. Indeed the total effect includes the positive impact associated with the reduction in marginal cost which should have fostered the activity and input levels with a magnitude depending on the demand price elasticity.

The effect on the relative demand for skills of the decrease in the cost of computers, is measured by $\psi_c = \eta_{sc} - \eta_{uc}$. Table 7 shows this elasticity to be unambiguously negative : it has a median value of -0.24. Besides, it is quite heterogeneous across the sample, with the first quartile around -0.40. Table 7 also shows that no such impact on the relative demand for skills is significant for the other forms of capital : the quartiles of the elasticity ψ_o do not differ significantly from zero.

Considering the median value of the parameter ψ_c, a decrease in the computer price by 15% should induce a shift in the relative demand for skills by $\psi_c \Delta \ln(p_c)$ equal to 3.9% with a 5%

confidence interval of [1.5%, 6.0%]. In other words, according to our results, the shift in the relative demand for skills therefore lays between 1.5% and 6.0%. At the aggregate level, this shift can be measured as $\Delta \ln\left(x_s/x_u\right) - \sigma_{u,s}^{M} \Delta \ln\left(p_u/p_s\right)$. In France, the relative cost of skilled to unskilled workers decreased on average by 0.03% a year on average between 1990 and 1999 whereas the ratio of skilled to unskilled labor increased by 2.2% a year (see figure 1). Since the median Morishima elasticity of substitution between unskilled and skilled labor is 3.2, the shift in the relative demand for skills can be evaluated at around 2.1%. This figure lies within our confidence interval. Our results are therefore consistent with the macroeconomic evolution. They also indicate that computerization does matter as far as the skill structure is concerned.

The parameter $\psi_c \Delta \ln(p_c)$ represents the median change in the ratio of skilled to unskilled employment if the relative labor supply is assumed perfectly elastic and held constant. Under the polar assumption of perfect inelasticity of the relative labor supply, the skill premium would increase by $\psi_c / \sigma_{u,s}^{M} \Delta \ln(p_c)$ which is found to be rather concentrated around 1.3%.

As has been heavily stressed above, we focus on the impact of the decrease in the price of computers, which we consider to be the true exogenous shock. This leads us to investigate the issue of biased technological change through the parameter ψ_c. We now relate this parameter to alternative measures used in the literature.

Studies looking at the skill bias generally rely on the direct estimation of an equation of the form:

$$d \ln\left(x_s/x_u\right) = \sigma_{us}^{D} d \ln\left(p_u/p_s\right) + \varphi_c d \ln x_c + \varphi_o d \ln x_o + \lambda_y d \ln y \qquad [8]$$

This equation represents the relative demand for skills with quasi-fixed capital stocks[15]. The elasticity φ_c measures the response in the demand for skills to a change in the quantity of computers x_c, quantities of other capital and output being held constant. In the framework of equation [8], the accumulation of computer capital is said to be biased toward skilled labor when $\varphi_c > 0$. Most micro-econometric studies indeed find a positive correlation between skilled intensity and computer use[16].

Let us show that this popular concept of technological bias (φ_c) holds a simple relation with ours (ψ_c), and can also be derived from the estimation of the technology of production and the level of inputs[17]. More generally, the parameters (φ_c, φ_o) can be related to (ψ_c, ψ_o) through the own- and cross- price elasticities of capital stocks to their prices[18]:

$$\left.\frac{\partial \ln\left(x_s/x_u\right)}{\partial\left(\ln p_c, \ln p_o\right)}\right|_{p_u, p_s, y} = \left.\frac{\partial \ln\left(x_s/x_u\right)}{\partial\left(\ln k_c, \ln k_o\right)}\right|_{p_u, p_s, y} \left.\frac{\partial\left(\ln k_c, \ln k_o\right)}{\partial\left(\ln p_c, \ln p_o\right)}\right|_{p_u, p_s, y}$$

that is to say :

$$\begin{pmatrix}\psi_c & \psi_o\end{pmatrix} = \begin{pmatrix}\varphi_c & \varphi_o\end{pmatrix}\begin{pmatrix}\eta_{cc} & \eta_{co} \\ \eta_{oc} & \eta_{oo}\end{pmatrix}$$

This last equation shows that, unlike φ_c which is computed assuming that capital stocks are constant, the elasticity ψ_c takes into account the substitution effects between computers and the other forms of capital[19]. As the own price elasticity of computers is close to –1 and the cross price elasticity between computers and the other forms of capital is not significantly different from zero, both measures are close within our framework. This is obvious when comparing estimates of ψ_c in table 7 and estimates of φ_c in table 8 for the median firm.

Table 8 also shows that the production function based estimate of parameter φ_c is relatively homogenous across our sample of firms. It therefore makes sense to compare this estimate with the value provided by the direct estimation of equation [8].

Direct estimates of equation [8] based on three different estimators are displayed in the right hand side sub-table of table 8. The within estimator points to a significant shift in labor demand toward skilled workers, much weaker however than the one obtained through the production function approach : the direct estimate of φ_c (0.02) is ten times lower than the median value (0.23) of its estimate based on the production function. Our approach therefore leads to a much larger extent of the skill bias than the traditional approach followed in the literature.

Estimating equation [8] raises endogeneity issues related to both relative wage and capital stocks. Indeed, relative employment and relative wages are determined at equilibrium. Moreover firms simultaneously choose capital stocks. The direction of the resulting estimation bias on the parameter φ_c is in general unclear. GMM estimations, aimed at correcting for simultaneity biases by means of internal instruments, perform poorly. The coefficients are very imprecise when the equation is estimated in levels and instrumented by lagged first-differences. The Arellano and Bond approach (first-differenced model instrumented by lagged levels) leads to poor overidentification tests as well as coefficients inconsistent with the previous estimation. The GMM approach proves here fully inconclusive, when it comes to explaining the discrepancy observed in the measure of φ_c according to the production function and the direct approach. The lack of external instruments is a recurrent problem in this study, which we have not been able to overcome.

Assuming however that simultaneity biases are of limited magnitude when the estimation is carried out in the intra-individual dimension, one may interpret the discrepancy between the direct and the production function approaches in terms of imperfect information from the managers' side. The latter may indeed not be fully aware of the true technological complementarities between labor and computers. Firms may consequently not have exhausted all the possibilities of substitution allowed by computerization.

Comparing the manufacturing and non manufacturing industries

Table 9 displays the results based on the within production function estimations carried out for the manufacturing and non manufacturing sectors separately(table 3b). There are some differences between both subsamples. The median value of the supply effect (parameter χ_c) is 4% in both sets of industries. The first and third quartiles are however 0% and 7% in the former against 2% and 4% in the latter.

As a rule, effects are stronger and more dispersed in manufacturing than in non manufacturing sectors. The computer price elasticities of skilled and unskilled labor demand (not reported) have higher median values for firms belong to the manufacturing industries, but also higher interquartiles spread. The computer price elasticity of skilled labor demand is also no longer significantly negative in the non manufacturing sector. This results in the skill bias parameter ψ_c being larger in manufacturing than in non manufacturing, where it is insignificant (table 9).

V. Summary and conclusions

In this paper, we have developed a methodology enabling us to measure at the firm level the effect of a decrease in the price of computers on various important firm characteristics : the marginal cost of production, the demand for aggregate labor and the skill structure. This methodology is based on the estimation of a production function from which we derive the elasticities of the above variables of interest to the price of computers. We find that the observed fall in computer prices constitutes a large supply shock. We also find large effects on the demand for inputs. The accumulation of computers induced by the fall in their prices appears to be biased towards capital against labor, and within labor biased against unskilled labor toward skilled labor. The fall in the price of computers is thus associated with an upward shift in the demand for skilled workers while it is associated with a negative shift in the demand for unskilled ones. This appears to be very specific to computers. Analog effects have been investigated for the price of "usual" capital goods. No pattern of substitutions similar to that found for computers may be identified. Our approach leads to larger effects on the relative demand for skills than the ones usually found in the literature and based on the direct estimation of a labor demand equation.

Our results call for further developments. Comparing the elasticity of production to computers to their cost share suggests that some complementary input correlated with computer stocks, such as organizational change, may matter as much as computers themselves. The existence of such unobserved inputs may explain why the elasticity of production to computers is higher than their cost share. It may also imply that the effects on the skill structure specifically associated with the accumulation of computers, may have been overestimated if organizational change also affects skilled and unskilled workers differently. Making this link explicit between computerization and organizational change is thus particularly important since it is a pre-requisite if we are to assess the influence of future decreases in the price of computer power. If the technological bias actually reflects the existence of an organizational bias, computerization may indeed become skill-neutral when associated opportunities of reorganizations are exhausted.

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Tables

Table 1: Definitions of the parameters of interest

Effect of a marginal change in p_c on		
the marginal cost $\chi_c(f, x^*)$	the demand for aggregate labor $\eta_{lc}(f, x^*)$	the relative demand for skills $\psi_c(f, x^*)$
$\left.\frac{\partial \ln C_y}{\partial \ln p_c}(x^*)\right\|_{p_u, p_s, p_o, y^*}$	$\left.\frac{\partial \ln(x_u + x_s)}{\partial \ln p_c}(x^*)\right\|_{p_u, p_s, p_o, y^*}$	$\left.\frac{\partial \ln(x_s / x_u)}{\partial \ln p_c}(x^*)\right\|_{p_u, p_s, p_o, y^*}$

Table 2: Summary statistics on the sample

			Whole sample			Manuf.	Serv.	Number of employees		
								<20	20-100	>100
	Quantiles		25%	50%	75%	50%		50%		
Annual Growth rate	Labor productivity	$y/(x_u + x_s)$	-0,04	0,00	0,05	0,01	0,00	0,00	0,00	0,01
	Computer stock	x_c	0,06	0,12	0,20	0,13	0,12	0,10	0,12	0,13
	Other Cap. Stock	x_o	-0,03	0,03	0,09	0,04	0,01	-0,01	0,02	0,04
	Skilled to unskilled	x_u/x_s	-0,04	0,02	0,09	0,02	0,02	0,01	0,01	0,03
	Cost of sk. to unskilled	p_u/p_s	-0,03	0,00	0,03	0,00	0,00	-0,01	0,00	0,00
Average	Share of unskilled	$x_u/(x_u + x_s)$	0,55	0,71	0,81	0,74	0,68	0,60	0,71	0,73
	Cost of unskilled to value added	$p_u x_u / py$	0,30	0,45	0,56	0,46	0,44	0,35	0,44	0,46
	Cost of skilled to value added	$p_s x_s / py$	0,25	0,35	0,52	0,32	0,41	0,48	0,37	0,33
	Comp. stock to value added	$p_c x_c / py$	0,00	0,01	0,01	0,01	0,01	0,01	0,01	0,01
	Other Cap. stock to value added	$p_o x_o / py$	0,07	0,13	0,22	0,17	0,10	0,09	0,12	0,15
Number of firms				5112		2515	2597	352	2015	2745

Note: Growth rates are computed over the period 1994-1997. Ratios are computed each year and then averaged over the period.

Table 3a: Estimation of the Translog production function on the whole sample

			Between	Within	Long difference	Difference GMM	System Estimator
	ρ		-	-	-	0,27 (0,07)	0,50 (0,03)
1^{st} order coefficients	Unskilled		0,35 (0,01)	0,48 (0,01)	0,54 (0,02)	0,57 (0,25)	0,36 (0,04)
	Skilled		0,33 (0,01)	0,29 (0,01)	0,33 (0,01)	0,37 (0,16)	0,34 (0,05)
	Computers		0,15 (0,01)	0,03 (0,01)	0,02 (0,01)	-0,10 (0,15)	0,17 (0,03)
	Other capital		0,12 (0,01)	0,08 (0,01)	0,07 (0,01)	0,62 (0,25)	0,11 (0,03)
2^{nd} order coefficients	Unskilled,	Unskilled	0,092 (0,005)	0,074 (0,006)	0,080 (0,007)	0,094 (0,055)	0,072 (0,027)
		Skilled	-0,100 (0,008)	-0,103 (0,008)	-0,130 (0,011)	-0,244 (0,093)	-0,162 (0,043)
		Computers	-0,057 (0,007)	-0,014 (0,006)	-0,010 (0,008)	-0,019 (0,042)	-0,013 (0,036)
		Other Cap.	-0,019 (0,005)	-0,004 (0,007)	-0,007 (0,009)	0,023 (0,102)	-0,027 (0,032)
	Skilled,	Skilled	0,079 (0,006)	0,060 (0,005)	0,065 (0,008)	0,176 (0,089)	0,153 (0,036)
		Computers	-0,011 (0,008)	0,017 (0,006)	0,025 (0,010)	-0,018 (0,066)	-0,172 (0,058)
		Other Cap.	-0,028 (0,006)	-0,009 (0,007)	-0,016 (0,008)	-0,041 (0,103)	-0,089 (0,036)
	Computers,	Computers	0,021 (0,004)	-0,001 (0,003)	-0,005 (0,005)	-0,007 (0,028)	0,061 (0,022)
		Other Cap.	-0,010 (0,005)	0,011 (0,004)	0,014 (0,006)	0,040 (0,036)	0,060 (0,030)
	Other Cap.,	Other Cap.	0,036 (0,002)	0,007 (0,004)	0,011 (0,005)	0,113 (0,054)	0,031 (0,018)
Sargan statistic			-	-	-	28,9	119,1
Degrees of freedom			-	-	-	45	75
p-value			-	-	-	0,970	0,001

Note: Sample of 5112 firms followed over the period 1994-1997. The translog is estimated in a quasi-differentiated form, under the assumption that the time dependent perturbation follows an AR(1) process. The difference GMM estimator is based on the instrumentation of the evolutions of explanatory variables by their lagged levels (i.e. on the sets of orthogonality conditions S1 and S2). The system estimator combines the previous set of moment conditions with more othogonality conditions involving the instrumentation of the levels of explanatory variables by their past evolutions (the set of orthogonality conditions includes S1 to S4). The *levels of inputs have been centered before computing the products, so that first order coefficients can be interpreted as elasticities at the mean point of the sample. Sargan statistics, degrees of freedom and the corresponding p-values are shown in the last three lines of the table.*

Table 3b: Estimation of the Translog production function on manufacturing and non-manufacturing industries separately

			Manufacturing			Non Manufacturing		
			Within	Difference GMM	System Estimator	Within	Difference GMM	System Estimator
ρ			-	0,13 (0,07)	0,50 (0,04)	-	0,18 (0,11)	0,51 (0,04)
1st order coefficients	Unskilled		0,56 (0,02)	0,38 (0,31)	0,46 (0,05)	0,43 (0,02)	0,47 (0,20)	0,33 (0,04)
	Skilled		0,30 (0,01)	0,35 (0,16)	0,31 (0,06)	0,29 (0,01)	0,35 (0,14)	0,31 (0,05)
	Computers		0,03 (0,01)	-0,03 (0,12)	0,09 (0,04)	0,03 (0,01)	-0,01 (0,14)	0,19 (0,04)
	Other capital		0,08 (0,02)	0,54 (0,21)	0,14 (0,03)	0,06 (0,01)	-0,01 (0,16)	0,08 (0,03)
2nd order coefficients	Unskilled,	Unskilled	0,105 (0,012)	0,175 (0,057)	0,119 (0,045)	0,064 (0,006)	0,031 (0,056)	0,070 (0,027)
		Skilled	-0,095 (0,014)	-0,096 (0,109)	-0,245 (0,082)	-0,111 (0,010)	-0,148 (0,081)	-0,121 (0,042)
		Computers	-0,028 (0,012)	-0,046 (0,051)	-0,059 (0,051)	-0,009 (0,006)	0,015 (0,038)	0,000 (0,040)
		Other Cap.	-0,020 (0,015)	-0,091 (0,111)	0,066 (0,049)	0,001 (0,007)	0,011 (0,074)	-0,010 (0,031)
	Skilled,	Skilled	0,064 (0,007)	0,024 (0,096)	0,173 (0,056)	0,057 (0,006)	0,004 (0,076)	0,094 (0,037)
		Computers	0,037 (0,010)	0,069 (0,065)	-0,038 (0,061)	0,010 (0,008)	0,030 (0,053)	-0,088 (0,058)
		Other Cap.	-0,032 (0,012)	-0,067 (0,127)	-0,108 (0,050)	0,000 (0,008)	0,035 (0,069)	-0,093 (0,032)
	Computers,	Computers	-0,005 (0,005)	-0,020 (0,030)	-0,006 (0,025)	-0,001 (0,004)	-0,008 (0,024)	0,047 (0,025)
		Other Cap.	0,024 (0,009)	0,034 (0,047)	0,113 (0,044)	0,003 (0,005)	0,043 (0,033)	0,052 (0,033)
	Other Cap.,	Other Cap.	0,007 (0,010)	0,057 (0,068)	-0,053 (0,033)	0,005 (0,005)	0,007 (0,037)	0,021 (0,018)
Sargan statistic			-	47,9	98,6	-	23,8	83,3
De of freedom			-	45	75	-	45	75
p-value			-	0,36	0,04	-	0,996	0,24

Note: Two subsamples of 2297 firms in the manufacturing industries and 2958 firms in the non manufacturing industries, followed over the period 1994-1997. The translog is estimated in a quasi-differentiated form, under the assumption that the time dependent perturbation follows an AR(1) process. The difference GMM estimator is based on the instrumentation of the evolutions of explanatory variables by their lagged levels (i.e. on the sets of orthogonality *conditions S1 and S2). The system estimator combines the previous set of moment conditions with more othogonality conditions involving the instrumentation of the levels of explanatory variables by their past evolutions (the set of orthogonality conditions includes S1 to S4). The levels of inputs have been centered before computing the products, so that first order coefficients can be interpreted as elasticities at the mean point of the sample. Sargan statistics, degrees of freedom and the corresponding p-values are shown in the last three lines of the table.*

Table 4 : Quantiles across the whole sample of firms of the measures of the supply shock associated with the variation in the price of computers

Quantiles	25%	50%	75%
χ_c	0,04 (0,02)	0,05 (0,01)	0,06 (0,01)
ε_c/θ	0,02 (0,01)	0,04 (0,01)	0,05 (0,01)
$\varepsilon_c/(\theta\pi_c)$	2,34 (1,24)	4,40 (1,31)	7,80 (1,89)

Note: Parameters are computed on the basis of the full-sample within estimation of the translog production function (4112 firms) using formula [1]. Standard errors are computed by bootstrap with 500 replications.

Table 5 : Quantiles across the whole sample of firms of the crossed Allen-Uzawa Elasticities of Substitution

Quantiles	25%	50%	75%
σ_{us}^{A}	2,6 (1,3)	3,4 (0,3)	4,9 (0,6)
σ_{uc}^{A}	2,1 (2,6)	3,5 (0,7)	5,9 (1,4)
σ_{uo}^{A}	1,1 (0,9)	1,4 (0,5)	1,9 (0,9)
σ_{sc}^{A}	-5,7 (2,1)	-1,7 (0,8)	-0,1 (5,2)
σ_{so}^{A}	1,1 (1,0)	1,4 (0,7)	1,8 (1,6)
σ_{co}^{A}	-6,3 (3,4)	-2,2 (1,5)	-0,7 (4,2)

Note: Allen-Uzawa Elasticities of Substitution are computed using formula [2] on the basis of the full-sample (4112 firms) within estimation of the technology of production. Standard errors are computed by bootstrap with 500 replications.

Table 6 : Quantiles across the whole sample of firms of factor demands elasticities to the price of computers

Quantiles	25%	50%	75%
η_{uc}	0,12 (0,05)	0,15 (0,04)	0,20 (0,06)
η_{sc}	-0,18 (0,07)	-0,08 (0,04)	-0,01 (0,05)
η_{cc}	-1,13 (0,26)	-1,00 (0,16)	-0,93 (0,26)
η_{oc}	-0,17 (0,13)	-0,09 (0,08)	-0,04 (0,07)

Note: Price elasticities are computed on the basis of the full-sample within estimation of the translog production function (4112 firms) using formula [3]. Standard errors are computed by bootstrap with 500 replications.

Table 7 : Quantiles across the whole sample of firms of labour demand elasticities to the price of computers

	25%	50%	75%
η_{lc}	0,06 (0,02)	0,07 (0,02)	0,08 (0,02)
η_{lo}	0,12 (0,04)	0,13 (0,04)	0,14 (0,04)
ψ_c	-0,39 (0,12)	-0,24 (0,08)	-0,16 (0,12)
ψ_o	-0,07 (0,15)	0,00 (0,11)	0,07 (0,17)
$-\psi_c / \sigma_{us}^M$	0,07 (0,02)	0,08 (0,03)	0,09 (0,03)

Note: Price elasticities are computed on the basis of the full-sample within estimation of the translog production function (4112 firms) using formula [5] and [6]. Standard errors are computed by bootstrap with 500 replications

Table 8: Estimation of the demand for skills

	Production function based estimator			Direct estimations		
	25%	50%	75%	Within	Difference GMM	System Estimator
ρ	-	-	-	-	0,11 (0,12)	0,83 (0,02)
σ_{us}^{D}	2,43 (0,67)	2,94 (0,31)	3,97 (0,56)	0,54 (0,03)	-0,44 (0,31)	0,21 (0,18)
φ_c	0,19 (0,09)	0,26 (0,09)	0,40 (0,13)	0,02 (0,01)	-0,47 (0,11)	0,41 (0,16)
φ_o	-0,11 (0,13)	-0,05 (0,10)	-0,01 (0,11)	-0,02 (0,01)	0,07 (0,24)	-0,24 (0,15)
λ_y	-0,27 (0,20)	-0,11 (0,18)	-0,02 (0,23)	0,01 (0,01)	0,00 (0,21)	-0,22 (0,10)
Sargan	-	-	-	-	19,4	38,8
Degrees of freedom	-	-	-	-	15	25
p-value	-	-	-	-	0,19	0,04

Note: Sample of 5112 firms over the period 1994-1997. Columns (1) to (3) display the quartile of the sample distribution of the parameters of interest computed from the estimated technology of production. Standard errors are obtained by bootstrap with 500 replications. The last three columns display the results of the direct estimation of the relative demand for skill. The demand equation is estimated in a quasi-differentiated form, under the assumption that the time dependent perturbation follows an AR(1) process. The difference GMM estimator is based on the instrumentation of the evolutions of explanatory variables by their lagged levels (i.e. on the sets of orthogonality conditions S1 and S2). The system estimator combines the previous set of moment conditions with more othogonality conditions involving the instrumentation of the levels of explanatory variables by their past evolutions (the set of orthogonality conditions includes S1 to S4). Sargan statistics degree of freedom and corresponding p-values are shown in the last three lines of the table.

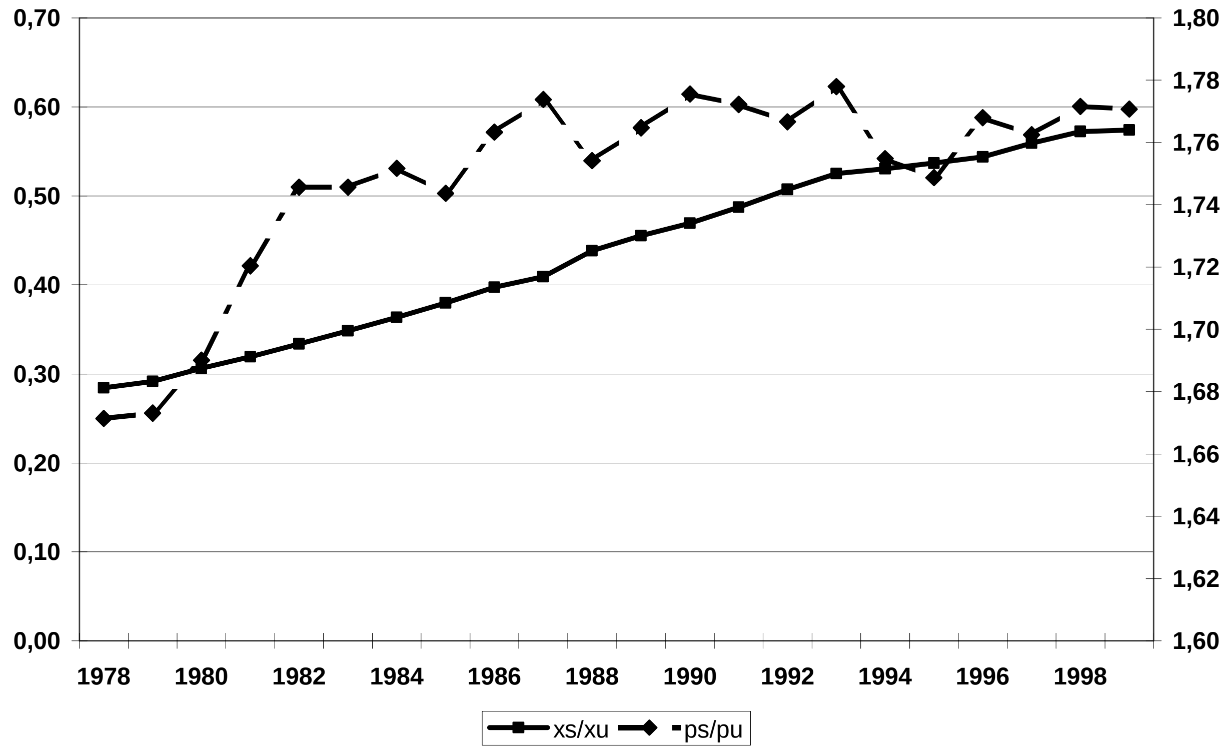
Table 9 : Quantiles of the parameters based on separate production function estimations for manufacturing and non manufacturing industries (within estimator)

	Manufacturing			Non Manufacturing		
Quantiles	25%	50%	75%	25%	50%	75%
χ_c	-0,00 (0,01)	0,04 (0,02)	0,07 (0,02)	0,03 (0,02)	0,04 (0,02)	0,05 (0,02)
ε_c/θ	0,00 (0,02)	0,03 (0,01)	0,06 (0,01)	0,03 (0,02)	0,04 (0,01)	0,05 (0,01)
η_{lc}	0,01 (0,03)	0,11 (0,04)	0,14 (0,06)	0,04 (0,03)	0,05 (0,03)	0,06 (0,03)
η_{lo}	0,09 (0,06)	0,15 (0,07)	0,21 (0,10)	0,08 (0,04)	0,09 (0,04)	0,11 (0,05)
ψ_c	-0,67 (0,20)	-0,36 (0,13)	0,10 (0,22)	-0,26 (0,16)	-0,17 (0,11)	-0,14 (0,13)
ψ_o	-0,23 (0,30)	0,05 (0,19)	0,75 (0,35)	-0,01 (0,19)	0,00 (0,14)	0,00 (0,17)
$-\psi_c / \sigma_{us}^M$	0,11 (0,04)	0,13 (0,05)	0,16 (0,07)	0,05 (0,04)	0,05 (0,04)	0,07 (0,04)

Note: Two subsamples of 2297 firms in the manufacturing industries and 2958 firms in the non manufacturing industries, followed over the period 1994-1997. The parameters are computed on the basis of the within estimation of the translog production function according to formula [1], [3], [5] and [6]. Standard errors are computed by bootstrap with 500 replications.

Figures

Figure 1: Evolution of relative employment and cost of skilled labor in France between 1977 and 1999



Source: Dhune et Heckel (2002)

Technical appendix

Appendix 1

We derive the elasticities of the marginal cost and factor demands to factor prices and output. Let us consider the conditional cost minimization program :

$$\min_{\{x_u, x_s, x_c, x_o\}} \left(p_u x_u + p_s x_s + p_c x_c + p_o x_o \right)$$
$$s.t. \quad y = f\left(x_u, x_s, x_c, x_o \right)$$

The first-order conditions of this program are :

$$\begin{cases} y = f \\ p_i = \lambda f_i \quad \text{for all } \; i \in \{u, s, c, o\} \end{cases}$$

where λ is the Lagrange multiplier, equal to the marginal cost C_y (envelope theorem). Differentiating the first-order conditions yields:

$$\begin{cases} dy = \sum_i f_i dx_i \\ dp_i / C_y = f_i \, dC_y / C_y + \sum_j f_{ij} dx_j \quad \text{for all } \; i \in \{u, s, c, o\} \end{cases}$$

or in matrix form :

$$\begin{bmatrix} dy \\ dp/C_y \end{bmatrix} = F \begin{bmatrix} dC_y/C_y \\ dx \end{bmatrix}$$

where F is the bordered Hessian (see footnote 5 of the main text). Inverting this relationship and using the co-factors and the determinant of this matrix, one can express the derivatives of the marginal cost and the demand for inputs, with respect to prices and output :

$$\begin{cases} \partial C_y / \partial p_i = F_i / |F| \\ \partial C_y / \partial y = C_y F_0 / |F| \\ \partial x_i / \partial p_j = F_{ij} / \left(C_y |F| \right) \\ \partial x_i / \partial y = F_i / |F| \end{cases}$$

Transforming these expressions into logarithmic derivatives and using again the first-order conditions of the cost minimization program, we finally obtain expressions [2] and [4] given in section 1 of the text:

$$\begin{cases} \chi_i \equiv \partial \ln C_y / \partial \ln p_i = f_i \, F_i / |F| \\ \delta_y \equiv \partial \ln C_y / \partial \ln y = f F_0 / |F| \\ \eta_{ij} \equiv \partial \ln x_i / \partial \ln p_j = \left(f_j / x_i \right) \left(F_{ij} / |F| \right) = \left(x_j f_j / f \right) \left(\sum_k x_k f_k / f \right)^{-1} \left(\sum_k x_k f_k / x_i x_j \right) \left(F_{ij} / |F| \right) = \left(\varepsilon_j / \theta \right) \sigma_{ij}^A \\ \mu_{iy} \equiv \partial \ln x_i / \partial \ln y = \left(f / x_i \right) \left(F_i / |F| \right) \end{cases}$$

Appendix 2

We give here the expressions of the parameters of interest in the translog case. The expression of output elasticities is :

$$\varepsilon_i = \alpha_i + \sum_j \beta_{ij} \ln\left(x_j\right)$$

Remarkably, all other parameters can be expressed as functions of only these output elasticities and second-order coefficients of the translog. To see this, let us define first:

$$\Gamma = \begin{bmatrix} 0 & \mathrm{E}' \\ \mathrm{E} & \mathrm{B} \end{bmatrix}$$
$$\mathrm{E} = \left(\varepsilon_i\right)$$
$$\mathrm{B} = \left(b_{ij}\right); \quad b_{ij} = \begin{cases} \beta_{ij} + \varepsilon_i(\varepsilon_i - 1) & \text{if } i = j \\ \beta_{ij} + \varepsilon_i \varepsilon_j & \text{if } i \neq j \end{cases}$$

and γ_0, $\left(\gamma_i\right)$, $\left(\gamma_{ij}\right)$ the co-factors of 0, $\left(\varepsilon_i\right)$, $\left(b_{ij}\right)$ in Γ divided by the determinant of Γ.

Elasticity of		Formula
scale	θ	$\sum \varepsilon_i$
marginal cost to factor price	χ_i	$\varepsilon_i \gamma_i$
marginal cost to output	δ_y	γ_0
substitution	σ^A_{ij}	$\theta \gamma_{ij}$
factor demand to price	η_{ii}	$\varepsilon_j \gamma_{ij}$
factor demand to output	μ_{iy}	γ_i

[1] This decline has been interpreted by some as paralleling the so-called "Moore's Law": Moore predicted that the number of transistors per integrated circuit would double every 18 months.

[2] This volume effect is besides a channel through which factor demands are affected by the decrease in the cost of computers (term $\mu_{iy} d \ln y$ in equation [2]).

[3] Note that we assume on the contrary that the cost of computers (and more generally all factor costs) in levels differs across firms as mentioned above.

[4] The growth accounting framework focuses on the contribution of the accumulation of computer capital to the growth of production, equal to $\varepsilon_c \Delta \ln x_c$ where ε_c denotes the elasticity of production to the stock of computers. However the increase in the stock of computers is not exogenous. The interest of a measure based on χ_c is that it is directly related to the exogenous shock $\Delta \ln p_c$.

[5] The bordered Hessian is a function of first and second order derivatives of the production function:

$$F = \begin{bmatrix} 0 & \nabla f' \\ \nabla f & \nabla^2 f \end{bmatrix}$$

[6] Similar parameters (η_{lo}, ψ_o) can be defined for the other capital goods.

[7] By contrast with the AUES, the MES measures the elasticity of a two-input ratio to the price of one of the two considered inputs, as shown by equation [7]. The MES is therefore a *two-input-one-price* elasticity.

[8] See Crépon and Heckel (2002) for more details.

[9] It is actually available since 1993 but the data concerning 1993 is known to be of poor quality.

[10] Notice that an alternative estimation strategy could be based on the estimation of the model using only first order conditions, expressing the share of each or some factors as linear functions of the crossed terms, the first order coefficient being identified by intercepts. In order to estimate these first order coefficients, it would however be necessary to include the share of all factors and thus to deal with the adjustment cost issue. Moreover, the residuals in the equation have no clear interpretation.

[11] Additional controls involving interactions of hours with other variables proved to be insignificant. They were therefore discarded from the specifications used in this paper.

[12] Our main conclusions would not be changed by preferring long difference.

[13] Note however that the effect we measure is partial in the sense that output and other inputs prices are held fixed.

[14] Indeed, in a multi-factor context, AUES are only *one-input-one-price* elasticities of substitution, which means that they have an economic interpretation only through price elasticities.

[15] The parameter σ_{us}^{D} in this setting is the direct elasticity of substitution (DES).

[16] See e.g. Caroli and Van Reenen (2001), Doms, Dunne and Troske (1997), Dunne, Haltiwanger and Troske (1996), Greenan, Mairesse and Topiol-Bensaid (2001), Haskel and Heden (1999), Kaiser (1998) and Machin (1996) and the overview in Chennels and Van Reenen (1999).

[17] To our knowledge, only Bresnahan, Brynjolfsson and Hitt (2002) and Caroli and Van Reenen (2001) have investigated so far the existence of complementarities between skills and computers using a production function framework. These papers do not however make explicit the relationship between the technology they postulate and the demand for skills.

[18] It is therefore possible to compare the evaluation of the intensity of the skill bias associated with computers implied by a direct estimation of equation [8] with a measure of the parameter based on the estimation of the technology of production (see below).

[19] Note that the derivation of the parameters entering equation [8] only requires that the firm adjust labor but not necessarily capital, as opposed to the derivation of the various elasticities to computer price.