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Using proxy variables to control for unobservables when estimating productivity: A sensitivity analysis*

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Abstract

The use of proxy variables to control for unobservables when estimating a production function has become increasingly popular in empirical works in recent years. The present paper aims to contribute to this literature in three important ways. First, we provide a structured review of the different estimators and their underlying assumptions. Second, we compare the results obtained using different estimators for a sample of Spanish manufacturing firms, using definitions and data comparable to those used in most empirical works. In comparing the performance of the different estimators, we rely on various proxy variables, apply different definitions of capital, use alternative moment conditions and allow for different timing assumptions of the inputs. Third, in the empirical analysis we propose a simple (non-graphical) test of the monotonicity assumption between productivity and the proxy variable. Our results suggest that productivity measures are more sensitive to the estimator choice rather than to the choice of proxy variables. Moreover, we find that the monotonicity assumption does not hold for a non-negligible proportion of the observations in our data. Importantly, results of a simple evaluation exercise where we compare productivity distributions of exporters versus non-exporters shows that different estimators yield different results, pointing to the importance of making suitable timing assumptions and choosing the appropriate estimator for the data at hand.

Keywords: Total factor productivity; Semiparametric estimator; Simultaneity; Timing assumptions; Generalized Method of Moments.
JEL Classification: C13, C14, D24, D40.

1 Introduction

Total factor productivity (TFP) is an important tool for researchers in evaluating the implications of various policy measures on firm performance. However, obtaining reliable measures of firm-level TFP is not easy, since firm-level productivity is typically unobserved by the econometrician. One approach that has been used to tackle this problem consists in estimating productivity as a residual of a production function. While it is possible to estimate a production function using Ordinary Least Squares (OLS), this results in an endogeneity bias due to the fact that productivity is known to the firms when they choose their inputs. As a consequence, estimation of a production function and the resulting TFP residual has itself been the topic of a large and still growing literature.[1] One of the most important contributions to this literature in the last 15 years has been the use of estimators that model the unobserved productivity by using observable firm-level variables. It is on this class of estimators (often defined as semiparametric estimators) that the current paper focuses.

The first semiparametric estimator was introduced by Olley and Pakes (1996, henceforth OP). They address the simultaneity issue by developing a two-step estimator of a production function, whereby firm's (observed) investment is used to proxy for its unobserved productivity. Since its publication, their estimator has been applied in many papers (see for instance Pavcnik, 2002, De Loecker, 2011 and Konings and Vandenbussche, 2008). A citation analysis in Google Scholar in July 2011 revealed 1,911 references to the original paper of OP.

Several adaptations and extensions to the estimator of OP have been developed meanwhile. Levinsohn and Petrin (2003, henceforth LP) use intermediate inputs (e.g. materials and energy) rather than investment to proxy for unobserved productivity. The semiparametric estimator of LP has also been applied extensively in empirical work, see for instance Fernandes (2007) and Javorcik and Spatareanu (2008), among others. More recently, the timing assumptions underlying the semiparametric estimators of OP and LP have been questioned by Ackerberg, Caves and Frazer (2006, henceforth ACF) who suggest an alternative two-step estimator where all relevant parameters are recovered in the second stage.[2] Wooldridge (2009) on the other hand fo-

[1] For a review of the literature, we refer to Van Beveren (2011) and Van Biesebroeck (2007).

[2] See Konings and Vanormelingen (2009) and Dumont, Merlevede, Piette and Rayp (2010) for some recent applications.

cuses on the inefficiencies associated with the two-step estimation procedure of existing methodologies and proposes a framework in which production function estimates can be obtained in one step. His framework allows for the timing assumptions of both the original semiparametric estimators and of the adapted framework of ACF and it has been applied to empirical data by Acharya and Keller (2009).

The present paper focuses on the class of estimators that have emerged since the seminal paper of Olley and Pakes (1996). We aim to contribute to the literature in three important ways. First, we provide a structured overview of these estimators and their underlying assumptions. While Ackerberg, Benkard, Berry and Pakes (2007, henceforth ABBP) provide an excellent review of the theoretical properties of most of the estimators that will be discussed below, they provide little guidance regarding their practical implementation. In our view, there are important aspects concerning the implementation of these estimators that need to be clarified, particularly for the one-step estimator proposed by Wooldridge (2009). Second, and more importantly, we want to evaluate how these estimators perform in practice, whether there are relevant differences between the estimates obtained and, to what extent differences in coefficient estimates yield different results in an evaluation exercise, where we compare the TFP distribution of exporters and non-exporters. Third, we introduce a simple test for the underlying assumption of all the estimators discussed that unobserved productivity is monotonically increasing in the proxy variable. Although Levinsohn and Petrin (2003) investigate the monotonicity assumption graphically, this is the first paper, to the best of our knowledge, that introduces a simple non-graphical test for the assumption that the unobserved productivity is monotonically increasing in the proxy variable.

The empirical part of the paper uses panel data for a sample of large Spanish manufacturing firms over the period 1990-2006. The data are obtained from the *Encuesta Sobre Estrategias Empresariales* (ESEE) and have been used in other empirical work, see for instance Ornaghi (2006), Ornaghi (2008) and Cassiman, Golovko and Martínez-Ros (2010). The data set is comparable to the typical data used by empirical researchers when estimating TFP, i.e. it provides information on outputs and inputs at the firm level in nominal value terms. Data on inputs and outputs in real terms are obtained by deflating these nominal values using appropriate industry-level price indices.[3]

[3]It should be noted that the ESEE data contain information on the *evolution* of firm-level prices. However, in the absence of information on initial firm-level prices, this infor-

Section 3 discusses the data and variables in greater detail.

The theoretical review presented in Section 2 highlights that the choice of which estimator to apply depends crucially on the timing assumptions made for the inputs in the production function, particularly for capital (through the capital rule) and labour (with or without dynamic implications). In our empirical analysis, we will remain agnostic on these timing assumption in order to compare production function coefficients and TFP estimates obtained using different estimators. Results reported in Section 4 show that estimates for structural parameters and related productivity tend to be more sensitive to the type of estimator than to the proxy variable used. In general, we find that coefficients vary more *between* estimators for the same proxy variable than *within* an estimator for different proxy variables. Our results suggest that the choice of one estimator over another can lead to very different outcomes when testing the hypothesis of constant returns to scale and when comparing the productivity distribution for exporting and non-exporting firms within an industry.

These results point to the importance of making suitable timing assumptions for the data at hand (and choosing the appropriate estimator based on these timing assumptions). As timing assumptions are likely to be industry- and country-specific, it is not straightforward for empirical researchers to make this choice. Moreover, it is not inconceivable that different firms within an industry allocate their inputs in different ways, in which case timing assumptions might be suitable for some firms, but not necessarily for all firms within a sector. Moreover, the monotonicity test we propose suggests that the fundamental assumption of a positive monotonic relationship between unobserved productivity and proxy variables seems to hold at large when we use materials as proxy variable. On the contrary, our test cast some doubts on the validity of this assumption when using investment or capacity utilization as proxy variable.

The rest of the paper is structured as follows. Section 2 provides a structured review of the different semiparametric estimators that have been developed in the literature. Section 3 introduces the data used in the empirical application and Section 4 uses these data to obtain insights into the relationship between the different estimators. Section 5 concludes.

mation cannot be exploited when estimating TFP in levels, unless firm-level fixed effects are included to control for initial price differences between firms.

2 Review of semiparametric estimators

2.1 General framework

As in previous works, we start out from a general Cobb-Douglas production function.[4]

$$Y_{it} = A_{it} K_{it}^{\beta_k} L_{it}^{\beta_l} M_{it}^{\beta_m} \tag{1}$$

where Y_{it} represents physical output of firm i in period t; K_{it}, L_{it} and M_{it} refer to capital, labour and materials respectively and A_{it} is the Hicksian neutral efficiency level of firm i in period t.

Taking natural logs of (1) results in a linear production function,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + u_{it} \tag{2}$$

where lower-case letters refer to natural logarithms and $ln(A_{it}) \equiv \beta_0 + \omega_{it} + u_{it}$. The constant can be thought to measure the mean efficiency level across firms while the remaining two terms measure unobservable (to the econometrician) producer-specific deviations from the mean.[5] The difference between the two unobservable terms is that ω_{it} refers to factors observed (or predictable) by the firm which are likely to affect the firms' input choices (for instance, managerial ability), while u_{it} is an i.i.d. component which captures unobserved factors to the firm and the econometrician, hence affecting the output of the firm but not the choice of the inputs (for instance, unexpected machine break-downs). Alternatively, u_{it} can represent measurement error in output or errors due to functional form discrepancies. In this case, as the average of these errors, $\bar{u}_{it}$, will in practice be captured by β_0, changes in the (industry- and/or time-specific) intercept will not measure true differences in efficiency if $\bar{u}_{it} \neq 0$.

Typically, empirical researchers estimate (2) for all firms in a specific industry and productivity levels can then be calculated as:

$$ln(\hat{A}_{it}) \equiv \hat{\omega}_{it} + \hat{\beta}_0 + \hat{u}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{3}$$

[4] ABBP show that semiparametric estimation methods carry over to other types of production functions, provided some basic requirements are met. Specifically, variable inputs need to have positive cross-partial derivatives with productivity, and the value of the firm has to be increasing in the amount of fixed inputs used. De Loecker and Warzynski (2009) and Rovegno (2011) estimate a translog production function using some of the semiparametric methodologies explained below.

[5] Typically, researchers will include year dummies in (2). In this case, the constant will be year-specific.

or alternatively, as

$$ln(\hat{A}_{it}) \equiv \hat{\omega}_{it} + \hat{\beta}_0 = exp(\hat{y}_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it})$$

depending on whether u_{it} are assumed to be respectively, unobserved factors contributing to the firms' efficiency or (mean zero) classical measurement errors.

The productivity measure resulting from the equations above can be used to evaluate the influence and impact of various policy variables directly at the firm level; or alternatively, firm-level TFP can be aggregated to the industry level by calculating the share-weighted average of $\hat{A}_{it}$.[6]

Although (2) can be estimated using Ordinary Least Squares (OLS), this method requires that the inputs in the production function are exogenous or, in other words, determined independently from the firm's efficiency level. Marschak and Andrews (1944) already noted that inputs in the production function are not independently chosen, but rather determined by the characteristics of the firm, including its efficiency, resulting in an endogeneity bias.

Intuitively, if the firm has prior knowledge of ω_{it} at the time input decisions are made, endogeneity arises since input quantities will be (partly) determined by prior beliefs about its productivity (Olley and Pakes, 1996; ABBP, 2007). Specifically, a positive productivity shock will likely lead to increased variable input usage; i.e. $E(x_{it}\omega_{it}) > 0$, where $x_{it} = (l_{it}, m_{it})$; introducing an upward bias in the input coefficients for labour and materials (De Loecker, 2011). In the presence of many inputs and simultaneity issues, it is generally impossible to determine the direction of the bias in the capital coefficient. Levinsohn and Petrin (2003) illustrate, for a two-input production function where labour is the only freely variable input and capital is quasi-fixed, that the capital coefficient will be biased downward if a positive correlation exists between labour and capital (which is the most likely setup).

The simultaneity problem has been the main focus of the methodological literature dealing with TFP estimation since the issue was raised by Marschak and Andrews (1944) more than sixty years ago. However, several other methodological issues arise when estimating a production function.

[6]Weights used to aggregate firm-level TFP can be either firm-level output shares, as in Olley and Pakes (1996); or employment shares, as in De Loecker and Konings (2006).

First, if no allowance is made for entry and exit of firms, a selection bias can emerge. The estimation algorithm of Olley and Pakes (1996) was the first to implement a formal correction for this bias, by including the estimated survival probability of the firm in the production function. However, very small changes in the production function coefficients are generally found after implementing the correction for the selection bias (see for instance De Loecker (2011) and Van Beveren (2011)). As a result and also because empirical data do not always allow for a clean definition of exit, the correction of Olley and Pakes (1996) has not been widely introduced in practice[7].

Second, as firm-level prices are generally not observed, econometricians must use industry-level price indices to obtain an approximate measure of firm-level quantities. This practice may bias the estimated coefficients of the production function when markets are not perfectly competitive. Klette and Griliches (1996) and De Loecker (2011) propose to control for the absence of firm-level output prices through the introduction of an industry-level output term, but this procedure has been criticized by others (Ornaghi, 2006). Finally, Bernard, Redding and Schott (2009) question the common practice of estimating production functions for all firms in a particular industry. Usually firms are assigned to a particular industry based on their most important sector of activity. However, recent work on multi-product firms (see for instance Bernard, Redding and Schott (2010b), Mayer and Ottaviano (2008), and Bernard, Van Beveren and Vandenbussche (2010a)) suggests that many firms (typically the larger firms) produce more than one product, often in more than one industry[8].

While the biases introduced by the use of industry-level prices and by estimating production functions for all firms in a particular industry can be sizeable, they fall beyond the scope of the present paper. As noted above, the primary focus of the semiparametric estimators has been to provide a solution for the simultaneity bias and for this reason, this is also the focus

[7]It should be noted that the distinction between the use of a balanced versus an unbalanced data set is important in empirical practice, yielding sizeable differences in the production function coefficients obtained. Essentially, when using an unbalanced data set, the data set implicitly allows for firm entry and exit, even in the absence of the formal correction introduced by OP

[8]In the absence of firm-product specific information on input use, obtaining reliable production function coefficients for multi-product and multi-industry firms remains an important challenge in future empirical work. Currently, the multi-product literature tends to rely on non-parametric approaches such as index numbers to avoid these caveats. Bernard et al. (2009) offer some potential solutions to this particular problem.

of our paper. Moreover, in the absence of information on firm-level prices and on the product mix of the firm (which is still typically the case in most firm-level data sets), it is not possible to control for these biases in empirical practice.

Before we discuss the different estimators in-depth, it is useful to highlight the two fundamental ingredients that all these estimators share. First, productivity ω is assumed to be known by the firm (though not by the econometrician) and to follow an exogenous first order Markov process.[9] The realization of productivity in the next period is fully determined by the information set available in period t, apart from the innovation in productivity between t and t+1, ξ_{it+1}, which is unexpected at time t. Specifically:

$$\omega_{it+1} = E(\omega_{it+1}|I_{it}) + \xi_{it+1} = E(\omega_{it+1}|\omega_{it}) + \xi_{it+1}$$

where the news component ξ_{it+1} is assumed to be uncorrelated with productivity and capital in period t+1.

The second, and most important, ingredient is that unobserved productivity can be proxied using an observable firm-level decision, i.e. the firm's dynamic choice of investment levels or its optimal allocation of variable inputs, such as materials or energy. This observed "proxy" variable p is assumed to be a strictly increasing function of unobserved productivity and the other state variable(s), such as capital. Specifically $p_{it} = f_t(\omega_{it}, k_{it})$ if capital is the only dynamic input entering the firm's state space.[10] Given the assumption of strict monotonicity, the relationship can be inverted, allowing for productivity to be expressed as a function of observables: $\omega_{it} = f_t^{-1}(p_{it}, k_{it})$.

Three clarifications about this function are in order. First, since the function f_t^{-1} has an unknown functional form, it can be approached either non-parametrically or parametrically. The origin of the term "semiparametric" to refer to this particular class of estimators can be found here. Given that the parametric approach, where the function f_t^{-1} is approximated using a higher-order polynomial in the proxy variable and the firm's state variables is used most often in practice,[11] our empirical exercise will compare the parametric

[9] Doraszelski and Jaumandreu (2009) have recently relaxed the assumption that the evolution of productivity is strictly exogenous by defining an econometric framework where firms can control (part of) the first order Markow process through their R&D investments.

[10] We will come back to the issue of static versus dynamic inputs and its implications for the estimation procedure below.

[11] An exception can be found in Levinsohn and Petrin (2003), who approximate this function non-parametrically using Kernel techniques.

version of all these estimators.

Second, the time subscript t suggests that this function should be allowed to vary over time. LP allow for this by estimating a production function for different periods of the macroeconomic cycle.[12] Third, the inversion of f_t requires that the productivity term ω_{it} is the only unobservable entering the inversion function $f_t(\omega_{it}, k_{it})$ ("scalar unobservable"). This is a rather restrictive assumption, since it essentially rules out measurement or optimization errors in these variables (Ackerberg et al., 2006), and it implicitly assumes perfect competition in inputs markets. In fact, in the presence of imperfect competition, firm-level prices of these inputs would determine the optimal level of the proxy variable and in turn would enter the inverted function f_t^{-1}. If these prices are unobserved by the econometrician, the scalar unobservable assumption would be violated, making it impossible to invert out the productivity shock. Note that this problem is likely to be more problematic when materials are used as a proxy variable than for investment, because of the (well documented) large dispersion of intermediate inputs prices within industries (see Ornaghi 2006).

Finally, it is useful to clarify some terminology regarding the timing and dynamic implications of the different inputs in the production function. As noted by ABBP (2007), inputs can be classified along two dimensions. The first dimension relates to the timing of the input decision. *Fixed* inputs are chosen before the productivity shock ξ_{it} is realized and are therefore uncorrelated with the innovation in the productivity term. *Variable* inputs on the other hand are chosen at the same time the productivity shock is realized and are therefore correlated with the innovation ξ_{it}. The second dimension relates to the dynamic implications of the inputs. Specifically, *static* inputs are chosen in period t, without any implications for the firm in period $t + 1$. *Dynamic* inputs on the other hand have dynamic implications, i.e. allocation of these inputs today will have implications for the next period. Dynamic inputs enter the state space of the firm. This distinction is important to characterize the different estimators that we will discuss hereafter.

[12] In our empirical exercise, we follow the common empirical practice of including time dummies in the first stage of the estimation algorithm. Hence, we will not estimate time-specific parameters for the polynomial term.

2.2 Olley and Pakes (1996)

As noted above, Olley and Pakes (1996) were the first to introduce the use of proxy variables to control for the unobservable productivity term in the production function. The estimation algorithm of OP additionally provides a solution to the selection problem, by taking into account the survival probability of the firm in the estimation algorithm. However, for reasons discussed in Section 2.1, we will not treat the selection problem here and focus instead on the simultaneity problem.

In terms of timing and the dynamic implications of the input variables Olley and Pakes (1996) assume that materials and labour are both static and variable while capital is a dynamic variable, fully determined by choices made in period $t-1$. Specifically, the law of motion for capital can be assumed to be:

$$K_{it} = (1-\delta)K_{it-1} + I_{it-1} \tag{4}$$

where δ is the yearly depreciation rate and I measures new capital investments. This law of motion assumes that it takes a full period for investments made by the firm to be translated into new capital. As a consequence, capital in period t is uncorrelated with the innovation in the productivity term between $t-1$ and t, ξ_{it}.

The novelty of the OP technique consists in defining the unobserved productivity by inverting out the investment demand function:

$$\omega_{it} = f_t^{-1}(p_{it}, k_{it}) \tag{5}$$

where p refers to the proxy variable investment i. Substituting the latter into (2) gives [13]:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f_t^{-1}\left(p_{it}, k_{it}\right) + u_{it} \tag{6}$$

Estimation of (6) proceeds in two steps. Assuming that the unknown function f_t^{-1} can be approximated parametrically by polynomial expansion of order J in p_{it} and k_{it}, i.e. $\omega_{it} = f_t^{-1}(p_{it}, k_{it}) \approx \sum_{j=0}^{J}\sum_{w=0}^{J-j}\gamma_{j,w}p_{it}^{j}k_{it}^{w}$, the first stage consists of OLS estimation of the equation:

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \Phi\left(p_{it}, k_{it}\right) + u_{it} \tag{7}$$

[13] It should be noted that OP use a value added production function and they include the age of the firm as an additional state variable.

where $\Phi(p_{it}, k_{it}) \equiv \beta_0 + \beta_k k_{it} + \sum_{j=0}^{J} \sum_{w=0}^{J-j} \gamma_{j,w} p_{it}^j k_{it}^w$.[14] Estimation of (7) results in a consistent estimate of the coefficients on labour and materials (the variable factors of production), as well as the composite term $\Phi(p_{it}, k_{it})$. Identification of β_k is prevented by the fact that k_{it} is collinear with the polynomial in p_{it} and k_{it}. Note that β_0 cannot be identified either as the polynomial expansion includes a constant term γ_0.

The second step of OP identifies the coefficient of capital using the estimates of $\hat{\Phi}(p_{it}, k_{it})$. As mentioned above, OP assume that productivity follows a first order Markov process:

$$\omega_{it} = E(\omega_{it} | \omega_{it-1}) + \xi_{it} = g(\omega_{it-1}) + \xi_{it} \tag{8}$$

where g is un unknown function and ξ_{it} represents the news component to productivity which was unforseen by the firm in period $t-1$. The particular timing assumption about investment decisions (see Section 2.1) implies that this term is orthogonal to capital:

$$E[\xi_{it} | k_{it}] = 0 \tag{9}$$

thus defining the moment condition necessary to identify the capital coefficient.

In practice, given an initial guess of the capital coefficient β_k', it is possible to compute $\omega_{it}(\beta_k)$ in all the periods (up to an intercept):

$$\omega_{it}(\beta_k) = \hat{\Phi}(p_{it}, k_{it}) - \beta_k' k_{it} \tag{10}$$

By using a polynomial of order J to approximate the g function in (8),[15] the ξ_{it} are then obtained as the residuals from the regression:

$$\hat{\omega}_{it}(\beta_k) = \sum_{j=0}^{J} \alpha_j \hat{\omega}_{it-1}(\beta_k)^j + \xi_{it}(\beta_k)$$

The coefficient of capital is estimated by using the sample analogue to (9), i.e. $\frac{1}{T}\frac{1}{N}\sum_t \sum_i \xi_{it}(\beta_k) k_{it} = 0$ and searching the value of β_k for which this is as close as possible to zero. Finally, standard errors can be obtained by applying bootstrapping techniques.

[14] In the empirical exercise we will use a third order polynomial.

[15] In the empirical exercise we will use J=3.

There are at least two important aspects that need to be considered when applying this procedure in any empirical exercise. First, the moment condition (9) can be replaced by:

$$E\left[\xi_{it} + u_{it} \middle| k_{it}\right] = 0 \tag{11}$$

where u is the i.i.d error term defined in equation (1). In the empirical application discussed in Section 4 we will experiment with the moments given by equations (9) and (11) to evaluate to what extent they yield different results.

Second, the coefficient of capital in the second stage can be estimated using a non-linear least square (NLLS) estimator. Starting from the estimates $\hat{\beta}_l$ and $\hat{\beta}_m$ obtained in the first stage, the production function (2) can be written as

$$\check{y}_{it} = \beta_k k_{it} + \omega_{it} + u_{it} \tag{12}$$

where $\check{y}_{it} \equiv y_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}$ and β_0 is omitted to simplify notation. Substituting in (8) results in:

$$\begin{aligned} \check{y}_{it} \quad &= \beta_k k_{it} + g(\omega_{it-1}) + \xi_{it} + u_{it} \\ &= \beta_k k_{it} + g(\Phi\left(p_{it-1}, k_{it-1}\right) - \beta_k k_{it-1}) + \xi_{it} + u_{it} \end{aligned}$$

Finally, by using the estimates of $\hat{\Phi}\left(p_{it}, k_{it}\right)$ and a polynomial to approximate the function g gives the empirical specification:

$$\check{y}_{it} = \beta_k k_{it} + \sum_{j=1}^{J} \gamma_j \left(\hat{\Phi}_{it-1} - \beta_k k_{it-1}\right)^j + \xi_{it} + u_{it} \tag{13}$$

which can be estimated using NLLS. Note that estimating equation (13) is the least square equivalent to minimizing the moment condition (11). The NLLS version of moment condition (9) would require using $(\check{y}_{it} - u_{it})$ on the left-hand side of (13) (where u_{it} is obtained in the first stage), instead of $\check{y}_{it}$. We will apply both the NLLS and GMM version of the OP estimator in the empirical application to verify to what extent they yield different results.

2.3 Levinsohn and Petrin (2003)

The main novelty introduced by Levinsohn and Petrin (2003) is the of use materials (or energy) as proxy variable, i.e. $p \equiv m$. Given that investments are generally lumpy and they often take the value of zero, there may be some doubts about the strict monotonicity assumption of the investment equation. The use of intermediate inputs to invert out ω seems a more reasonable approach. As materials is now an argument of the inverted function $\omega_{it} = f_t^{-1}(p_{it}, k_{it})$, it is no longer possible to identify β_m in the first stage, as it will be collinear with f_t^{-1}.[16] Specifically, the LP approach implies that equation (7) defined in Section 2.2 must be replaced by

$$y_{it} = \beta_l l_{it} + \Phi\left(p_{it}, k_{it}\right) + u_{it} \tag{14}$$

so that only the coefficient on labour will be identified in the first stage.

Identification of the parameters β_k and β_m in the second stage requires an additional moment condition to the one used by OP to identify the capital coefficient. LP use the value of intermediate inputs in $t-1$, given that this can be assumed to be orthogonal to shocks in innovation between $t-1$ and t. Accordingly, the LP estimator is based on the following moment condition:

$$E\left[\xi_{it}| \begin{array}{c} k_{it} \\ m_{it-1} \end{array}\right] = 0 \tag{15}$$

and estimation then involves searching for the pair (β_k, β_m) that makes the empirical analogue of (15) as close as possible to zero.

Two things need to be noticed about the LP approach. First, given that material is endogenous and needs to be instrumented with m_{it-1}, it is not possible to estimate the second stage parameters β_k and β_m using NLLS.[17] Second, LP assume that the dynamics of capital depend on the investment decision in period t:

$$K_{it} = (1-\delta)K_{it-1} + I_{it} \tag{16}$$

Under this framework, capital is predetermined to the extent that the firms are assumed to choose their investments before observing the productivity shock ξ_{it}. In other words, the correlation between capital and the shocks is not determined by the subscript of the investment variable, but by the point in time in which this investment is assumed to have been decided.

[16] Note that there are no differences with OP if energy is used as proxy variable.

[17] This problem does not arise when using a value added production function because m_{it} doest not enter the list of regressors.

2.4 Ackerberg, Caves and Frazer (2006)

Ackerberg et al. (2006), henceforth ACF, critically review the assumptions underlying the estimators proposed by OP and LP. They show that it is hard (or even impossible) to identify coefficients on labour in the first-step of these estimators because l is likely to be collinear with the non parametric terms (i.e. the polynomial in the proxy variable and capital). While this problem can arise in the context of both the OP and LP estimator, ACF argue that it is particularly problematic when variable inputs are used as proxy variables.

For the LP estimator, since labour and materials are both chosen simultaneously, a natural assumption would be that they are both functions of the same state variables:

$$\begin{aligned} m_{it} &= f_t\left(\omega_{it}, k_{it}\right) \\ l_{it} &= g_t\left(\omega_{it}, k_{it}\right) \end{aligned}$$

Hence, both labour and materials depend on the fixed input k and productivity ω. Using the invertibility condition of LP, i.e. $\omega_{it} = f_t^{-1}\left(m_{it}, k_{it}\right)$, this leads to the following result:

$$l_{it} = g_t\left(f_t^{-1}\left(m_{it}, k_{it}\right), k_{it}\right)$$

The equation above shows that it is not possible to identify the labour coefficient in the first stage as l is a function of the same variables that are used to proxy the unobserved productivity ω_{it} and it is therefore perfectly collinear with the inverted function f_t^{-1}. ACF further investigate to what extent plausible assumptions can be made about the data generating process for labour in order to save the LP first stage estimation, with little success.

This collinearity problem can also arise in the context of the OP estimation procedure. However, for the OP estimator, identification of the labour coefficient can be achieved by assuming that investment and labour are determined by different information sets. In particular, while investment in period t is chosen while knowing the productivity ω_{it}, the allocation of labour may be decided between $t-1$ and t when firms do not have perfect information about their future productivity. If this assumption holds for the data at hand, the labour coefficient can be identified in the first stage of the estimation algorithm in the case of OP. For LP, this assumption does not solve the collinearity problem, since choosing labour prior to choosing material inputs will make the choice of the latter directly dependent on the choice of labour inputs, i.e. $m_{it} = f_t^{-1}(\omega_{it}, k_{it}, l_{it})$, again preventing identification of the labour coefficient in the first stage. This difference between the two estimators stems from the fact that investment, unlike materials, is not directly linked to period t outcomes, so that a firm's allocation of labour will not directly affect its investment decisions.

ACF suggest an alternative estimation procedure which builds on the LP insight that it is more reasonable to use materials to invert out the unobserved productivity ω, but where the coefficient on labour is no longer estimated in the first stage of the algorithm. All input coefficients are obtained in the second stage, while the first stage only serves to net out the error component in the production function. The procedure proposed by ACF starts out from a basic value added production function, but it carries over to an output production function. Starting out from the output production shown in (2), ACF assume that labour is chosen by the firm at time $t - b$, where $0 < b < 1$ as it is "less variable" than materials (or energy), which is chosen at time t. This implies that labour is allocated prior to m, but after k_{it}. This assumption is based on the idea that it takes some time before firms' hiring and firing decisions take effect, though not as much time as is the case for capital. Accordingly, labour enters the set of variables that affect the choice of materials: $p_{it} = f_t^{-1}(\omega_{it}, k_{it}, l_{it})$.[18] Inverting this function for ω and substituting into equation (2) results in:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f_t^{-1}(p_{it}, k_{it}, l_{it}) + u_{it} \\ &= \Phi(p_{it}, k_{it}, l_{it}) + u_{it} \end{aligned} \tag{17}$$

Equation (17) shows that none of the coefficients can now be recovered from the first stage.[19] This is true even if labour does not have dynamic implications, since labour is assumed to be less variable than materials in the current framework (i.e. it is decided just before materials).

Since labour is estimated in the second stage, the ACF approach is robust to the assumption that labour is a dynamic input. Essentially, in the presence of large hiring and firing costs, labour is costly to adjust and it enters the

[18] In the empirical specification, we will use a 3th order polynomial: $\omega_{it} = f_t^{-1}(p_{it}, k_{it}, l_{it}) \approx \sum_{j=0}^{3} \sum_{w=0}^{3-j} \sum_{g=0}^{3-j-w} \gamma_{j,w,g} p_{it}^j k_{it}^w l_{it}^g$.

[19] Note that the coefficient β_m cannot be estimated in the first step even if the proxy variable used is not materials because this is likely to be perfectly collinear with the variables entering the inverted f function.

set of state variables on which the choice of the proxy variable depends. Therefore, the fact that labour enters the function $p_{it} = f_t(\omega_{it}, k_{it}, l_{it})$ can be due either to the assumption that l is a static input "less variable" than the proxy p or to the fact that labour is actually a dynamic input subject to large adjustment costs.

Estimation of (17) in the first stage allows for separating Φ from the unexpected deviations due to measurement errors, unexpected delays or other external circumstances which are subsumed in u_{it}. Following the estimate of Φ in the first stage, identification of β_k, β_l and β_l can be obtained using the moment conditions:

$$E\left[\xi_{it}| \begin{array}{c} k_{it} \\ l_{it-1} \\ m_{it-1} \end{array}\right] = 0. \tag{18}$$

Under the assumption that labour is chosen before the shock to innovation ξ_{it} is observed by the firm,[20], it is possible to use l_{it} instead of l_{it-1} in (18) above. In the empirical estimation we will refer to the estimates obtained using moment (18) as ACF and those obtained using the contemporaneous value of labour as ACF-L.

It is important to note that in the ACF framework, labour is included in the argument of f_t^{-1} because it is assumed to be "less variable" than materials and therefore, it is part of the information set that is known to the firm when choosing the latter. This is not the case under the original LP framework, where labour is a variable input determined at the same time as materials and with no dynamic implications. Regardless of whether labour is used to invert out the unobserved productivity, the essence of the ACF critique is that β_l cannot be identified in the first stage of LP as labour is perfectly collinear with $f_t^{-1}(p_{it}, k_{it})$. Since all the parameters are actually estimated in the second stage regression, it is possible to address the collinearity issue by using a single equation instrumental variables method. We come back to this point in the next section, when we introduce the econometric approach defined by Wooldridge (2009).

2.5 Wooldridge (2009)

[20]This can be the case if extensive training is required before workers can enter production.

Wooldridge (2009) defines an econometric framework where the two-step estimators described above are re-defined as two equations to be estimated in one step. After explaining the details of this new estimator in the context of LP (or OP), the end of this section clarifies how the Wooldridge procedure simplifies to a single equation method in the context of the ACF estimator.

Wooldridge (2009) notes that the two-step estimators, which require bootstrapping techniques to obtain standard errors, are inefficient for two reasons: (i) they ignore the contemporaneous correlation in the errors across two equations; and (ii) they do not efficiently account for serial correlation or heteroskedasticity in the errors. Wooldridge (2009) shows how these estimators can be implemented using a single set of moments to be estimated in one step. This should address the inefficiencies of the OP and LP estimators as it uses information on the covariance of the errors. His framework additionally allows for the inclusion of cross equation restrictions and to test the validity of the resulting specifications using the Sargan-Hansen test of overidentifying restrictions.

Specifically, the first equation of the system is identical to (6), the first stage equation of OP and LP. With proxy variable p and a polynomial of order J to model the unobserved productivity, i.e. $\omega_{it} = f_t^{-1}(p_{it}, k_{it}) \approx \sum_{j=0}^{J} \sum_{w=0}^{J-j} \gamma_{j,w} p_{it}^{j} k_{it}^{w}$, equation (6) can be written as

$$y_{it} = \delta_k k_{it} + \beta_l l_{it} + \delta_m m_{it} + \sum_{j=1}^{J} \sum_{w=1}^{J-j} \gamma_{j,w} p_{it}^{j} k_{it}^{w} + u_{it} \tag{19}$$

where $\delta_k \equiv \beta_k + \gamma_k$ and $\delta_m \equiv \beta_m + \gamma_m$ if materials is the proxy variable.[21] If the proxy variable is not materials, then $\delta_m \equiv \beta_m$. To simplify notation, the equation above and those defined in the rest of this section will not include the constant term. As before, the constant and the coefficient β_k cannot be identified. If materials is the proxy variable, β_m additionally will not be identified in (19).

Under the assumption that the errors u_{it} are not observed by the firm, all the regressors on the right-hand-side of (19) are exogenous. The most straightforward choice of instrumental variables for (19) is simply:

$$z_{it1} \equiv (l_{it}, \boldsymbol{c_{it}}) \tag{20}$$

[21]In other words, δ_k includes the coefficient of capital in the production function, β_k, and in the polynomial term, labeled γ_k with a slight abuse of notation.

where $\boldsymbol{c_{it}}$ is a vector containing all the terms of the polynomial in (p_{it}, k_{it}). These instruments correspond to the OLS regression in LP for estimating β_l in the first stage.

The interesting insight of Wooldridge (2009) is that the assumption that productivity follows a first order Markov process as in (8) results in a second equation:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + g\left(\sum_{j=0}^{J}\sum_{w=0}^{J-j} \gamma_{j,w} p_{it-1}^{j} k_{it-1}^{w}\right) + \xi_{it} + u_{it}.$$

where all the coefficient βs of interests can be identified when using appropriate instruments.

In the empirical application we will assume that $g(\cdot)$ can be approximated by a 2nd order polynomial in v, i.e. $g(v) = \rho_0 + \rho_1 v + \rho_2 v^2$, thus resulting in:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \sum_{q=1}^{2} \rho_q \left(\sum_{j=0}^{J}\sum_{w=0}^{J-j} \gamma_{j,w} p_{it-1}^{j} k_{it-1}^{w}\right)^q + \xi_{it} + u_{it}. \quad (21)$$

It must be noticed that the equation above restricts the γ's parameters entering the linear and quadratic term of the function $g(v)$ to be the same.

The set of instruments for (21) would include fixed variables such as capital in period t, lagged variable inputs in period $t-1$, and functions of these inputs:

$$z_{it2} \equiv (k_{it}, l_{it-1}, \boldsymbol{c_{it-1}}, \boldsymbol{q_{it-1}}) \quad (22)$$

where $\boldsymbol{q_{it-1}}$ refers to nonlinear function of $\boldsymbol{c_{it-1}}$ and l_{it-1}.[22] While all the instruments used for (21) are also valid for (19), the contemporaneous m_{it} and l_{it} are only valid instruments for (19) as they are likely to be correlated with the innovation in the productivity ξ_{it}.

[22] Note that it is possible to include as many nonlinear function $\boldsymbol{c_{it-1}}$ as necessary to identify all the ρ parameters. Lagged values of the inputs up to year $t-2$ are also valid instruments but adding more lags is costly in terms of lost initial time periods.

Using the matrix of instruments

$$Z_{it} \equiv \begin{pmatrix} z_{it1} & 0 \\ 0 & z_{it2} \end{pmatrix},$$

and defining the residual function

$$\begin{aligned} r_{it}(\boldsymbol{\theta}) &= \begin{pmatrix} r_{it1}(\boldsymbol{\theta}) \\ r_{it2}(\boldsymbol{\theta}) \end{pmatrix} \\ &= \begin{pmatrix} y_{it} - \delta_k k_{it} - \beta_l l_{it} - \delta_m m_{it} - \sum_{j=1}^{J} \sum_{w=1}^{J-j} \gamma_{j,w} p_{it}^{j} k_{it}^{w} \\ y_{it} - \beta_k k_{it} - \beta_l l_{it} - \beta_m m_{it} - \sum_{q=1}^{2} \rho_q (\sum_{j=0}^{J} \sum_{w=0}^{J-j} \gamma_{j,w} p_{it-1}^{j} k_{it-1}^{w})^q \end{pmatrix} \end{aligned} \tag{23}$$

GMM estimation of the parameters in equation (19) and (21) requires solving the moment conditions:

$$E\left[Z_{it}' r_{it}(\boldsymbol{\theta})\right] = 0.$$

Provided sample averages are consistent estimators of population moments, the analogy principle suggests choosing the estimator $\hat{\boldsymbol{\theta}}$ to solve

$$\frac{1}{T}\frac{1}{N}\sum_{t}\sum_{i}\left[Z_{it}' r_{it}(\hat{\boldsymbol{\theta}})\right] = 0.$$

Following the analysis of ACF, none of the parameters of interest can be identified using (19) as l_{it} is likely to be a deterministic function of (k_{it}, m_{it}). Wooldridge (2009) notes that a simple way to address the ACF critique would then be to use a single equation instrumental variables method applied to equation (21). This allows the researcher to recover estimates for all production function coefficients while controlling for the multicollinearity of labour, even if labour does not have any dynamic implications.[23] Note that the assumption that labour is "less variable" than materials (or that labour is a dynamic input that affects the choice of materials) would require adding labour as an argument of the function used to invert out productivity $\omega_{it} = f_t^{-1}(p_{it}, k_{it}, l_{it})$. This means that equation (21) would be replaced by:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \sum_{q=1}^{2} \rho_q (\sum_{j=0}^{J} \sum_{w=0}^{J-j} \sum_{g=0}^{J-j-w} \gamma_{j,w,g} p_{it-1}^{j} k_{it-1}^{w} l_{it-1}^{g})^q + \xi_{it} + u_{it}. \tag{24}$$

In the empirical results, we will refer to the single equation estimator of (21) and (24) as respectively one-step Wooldridge LP (WOOL-LP) and one-step Wooldridge ACF (WOOL-ACF). It should be noted that if materials is

[23] We are thankful to Amil Petrin for pointing this out to us.

the proxy variable, it has to be instrumented in equations (21) and (24) using longer lags (starting in t-2), since m_{it-1} enters the polynomial. Similarly, in equation 24 only longer lags (starting in t-2) can be used to instrument the labour coefficient.

3 Data

The data used in the empirical application below come from the *Encuesta Sobre Estrategias Empresariales* (ESEE). The ESEE conducts annual surveys of a representative panel of Spanish manufacturing firms since 1990. The unit surveyed is the firm, not the plant or the establishment. Each year, about 1,800 firms (on average) are included in the survey. The data include information on firms' balance sheets and income statements, in addition to questions concerning their innovation management (product and process innovation, R&D efforts) and export behaviour (export turnover, main export markets). The data have been used in several empirical papers in recent years, see for instance Delgado, Fariñas and Ruano (2002), Dolado and Stucchi (2008), and Doraszelski and Jaumandreu (2009).

The sample used in Section 4 consists of an unbalanced panel observed for the period 1990-2006. The raw data set consists of 4,357 firms for a total number of 30,827 observations. We first select on availability of data required for the production function estimations (including availability of the different proxy variables). This implies that the sample used in the empirical estimations will be identical for the different proxy variables, hence excluding the possibility that differences in coefficients are due to sample selection issues rather than proxy variables used. Moreover, we only retain firms that are observed for at least 3 consecutive years. This leaves us with a final sample of 2,032 firms and 17,673 firm-year observations. It should be noted that in some cases the final sample size in the empirical estimations might be reduced due to the use of lagged variables as instruments, hence omitting one or more years from the sample.

Although the different estimators discussed in section 2 can be applied in the context of a value added or output production function, the estimates reported in section 4 use a value added production function throughout. This choice is driven by the fact that we can use NLLS estimators in the second step of LP approach even when materials is used as proxy variable. Therefore, the variables we use in the empirical specifications are real value added, labour, real capital together with three proxy variables: investment, materials and capacity utilization.

Firm-level investment and materials are the traditional proxy variables introduced by OP and LP respectively and so they are naturally both included. We use capacity utilization as an additional proxy variable. This variable measures the rate of utilization of the standard capacity of production at the firm level. Our definitions of firm-level output and inputs, as well as of the proxy variables, follows common practice in the literature. In particular, nominal values of value added and capital, obtained from firms' annual accounts data available in the ESEE survey, are deflated using appropriate price indices. For capital and investment, the price index only varies by year, while for value added and materials, the price index varies by sector and year.[24]

As was noted in Section 2, we construct two different measures of the capital stock: one using the law of motion (4) as in OP and the other based on equation (16) as in LP. This eclectic approach in the construction and choice of the variables used in the empirical exercise is important to understand how these estimators perform in different circumstances. Employment is measured as average number of workers (full-time equivalents) during the year. Materials are defined as consumption of intermediates at the firm level. Details on the definitions of these variables are provided in Appendix A.

For the purpose of our empirical analysis, firms are divided into 10 sectors.[25] Table 1 provides some insights into the sector distribution of firms in the sample used in the empirical analysis. The largest sector in terms of number of firms is the Food and Beverages sector, followed by the Ferrous and non-ferrous metals sector and Chemicals and plastics. In terms of average firm size (measured by the average number of employees or average

[24] Industry deflators for output, intermediary inputs and value added are obtained from the web page of the the Spanish Institute of Statistics, INE. It should be noted that the ESEE reports firm-level information on changes in (output/input) prices but we do not use this information in our empirical exercise. As the survey does not report the level of prices, our specifications would be still affected by measurement errors given that we do not use firm fixed effects to control for unobserved heterogeneity in prices. In this way, our empirical exercise mimics the approach used in most empirical exercises.

[25] The original industrial classification reported in the survey is based on 18 sectors. We combine certain sectors in order to retain sufficient observations in all sectors for the empirical estimations.

value added across all firm-year observations in the sector), the Transport sector is clearly the sector with the largest firms (on average), followed by the Electrical goods sector, although firms in the Transport sector employ on average three employees for one employee in the Electrical goods sector. Table 2 summarizes the key variables used in the production function estimations below. All variables are defined in logarithms, as they will be used in the empirical application. From the table, it is clear that the number of observations for all variables, including the proxy variables is identical.

4 Empirical application

The sample introduced in Section 3 will be used to estimate a value added production function using the different estimators reviewed in Section 2. Overall, there will be six different estimators: (i) the original OP-LP estimator, using Non-Linear Least Squares in the second stage of the estimation (OPLP-NLLS); (ii) the original OP-LP estimator, using GMM in the second stage of the estimation (OPLP-GMM); (iii) the Ackerberg-Caves-Frazer estimator where l_{it} is instrumented by l_{it-1} (ACF) or l_{it} is not instrumented (ACF-L); (iv) The two-equation Wooldridge estimator (WOOL); (v) The one-equation Wooldridge IV estimator where labour has dynamic implications (WOOL-ACF) and finally (vi) the one-equation Wooldridge IV estimator where labour does not have dynamic implication (WOOL-LP). Note that the the second stage of estimators (ii) and (iii) will be implemented twice, once using moment condition (9) and then using moment (11). Similarly, the NLLS estimator (i) will be run first using both $\check{y_{it}}$ and $(\check{y}_{it} - u_{it})$ on the left-hand side of equation (13).

For sake of clarity and brevity, Section 4.1 below only report results for one industry, Food and Beverages. Besides being the largest sector in the survey in terms of number of firms, an important feature of this sector is that it has low R&D expenditure. All the estimators above assume that productivity follows an exogenous Markov process. This assumption seems particularly questionable for industries with high R&D where productivity changes are in part governed by firms' innovative effort.[26] Given the importance of the monotonicity assumption for the construction of all these estimators, Section 4.2 describes a simple test to check whether productivity is indeed monotonically increasing with respect to the proxy variable.

[26]A recent paper by Doraszelski and Jaumandreu (2009) proposes a new econometric approach which accounts for the uncertainty and heterogeneity in the link between R&D and productivity.

Section 4.3 summarizes the results for other sectors. Finally, in Section 4.4 we present a simple evaluation exercise to investigate to what extent TFP estimates obtained using the different estimators, yield different results. To this end, we compare the productivity distributions of exporters versus non-exporters in our sample, using nonparametric techniques.

4.1 Comparing production function coefficients

Tables 3 and 4 report the estimated coefficients on labour and capital, respectively. Each row contains results for a specific estimator (and moment condition in some cases). The columns show results by proxy variable (investment, materials and capacity utilization) and for two different measures of capital, computed using the law of motion (4) and (16). Standard errors of the estimated coefficients (computed using bootstrapping techniques for the two-stage estimators) are not reported for brevity but we indicate with an asterisk whether the estimates are significant at 5 percent significance level or higher.

The first row of these tables reports the OLS estimates obtained with capital rule (4) and (16), which is a useful benchmark to compare the other estimators.[27] The WOOL-ACF estimator is found to give unreasonable coefficient estimates on both labour and capital for all different proxy variables and we will not comment further on this estimator. The second stage of the OPLP-GMM and ACF does not converge for some combinations of proxy variables and capital input. In these cases, results for the labour coefficients obtained in the first stage of the OPLP estimator are also not reported. The last column of the tables reports the mean within an estimator for different proxy variables and capital rule, while the last row reports the mean across different estimators for the same proxy variable and capital rule.

It should be noted that there exists no clear theoretical prior on the magnitude of the production function coefficients. Hence, we follow the common approach in the literature and compare the results to standard OLS results. The mean of the coefficients on labour and capital (excluding the OLS and the WOOL-ACF) are respectively 0.75 and 0.36. These values are very close to those obtained with OLS. Looking at the last row, we see that the three different proxy variables and the two capital rules tend to produce rather

[27]There is no proxy variable used for OLS, so that there are only two estimates for the labour coefficient and two estimates for the capital coefficient, depending on which capital rule is used.

similar point estimates of β_l and β_k. But there are also some interesting differences that emerge from the two tables. The OPLP-NLLS and OPLP-GMM produce lower point estimates of β_l than those obtained using OLS. At the same time, we find that capital coefficient tend to rise in going from OLS to OPLP-GMM, with results less clear-cut for the OPLP-NLLS. These results are broadly consistent with the idea that OLS will tend to overestimate β_l (given that there should be a positive correlation between unobserved productivity and labour usage) and will usually underestimate β_k (see Levinsohn and Petrin (2003) for further details).

By the same token, it is surprising that the ACF and ACF-L estimators tend to produce higher point estimates of β_l than OLS. Similarly surprising is the fact that ACF-L gives lower (higher) estimates of the labour (capital) coefficient than ACF given that there is a higher correlation between output and the number of workers in the same year. More generally, mean values reported in the last column seem to suggest that the estimator proposed by ACF is rather sensitive to the moment conditions and the instruments used. This first set of results seem to cast some doubt on the methodology suggested by ACF. We believe that the poor performance of the ACF estimator is due the the fact that β_l and β_k are estimated in the second step together with the coefficient on lagged capital and labour in $t-1$. All these variables are highly correlated and this may hamper the identification of the parameters of interest.

Table 3 and 4 show that the WOOL estimates of labour coefficient are very similar to the OLS coefficients while those of the WOOL-LP are lower than OLS, as for the OPLP. At the same time, these two estimators produce low point estimates for the capital coefficient compared to the other two-stage estimators. It must also be noticed that the Hansen test of over-identifying restrictions for the WOOL estimator (not reported in the tables) always rejects the null hypothesis that all excluded instruments are exogenous for any choice of the proxy variable and the capital rule. Finally, the estimated coefficients on labour and capital are respectively larger and smaller when capital is computed according to the OP rule (4). This result might be due to the fact that capital computed using the LP rule (16) is more directly linked to current output, thus reducing the importance of labour in explaining output changes.

The heterogeneity of the results obtained, depending on the estimator, moment conditions, proxy variable and capital rule becomes particularly clear when we test whether the obtained coefficients satisfy the constant returns to scale hypothesis. Results of this test are reported in Table 5. We find that the hypothesis is (almost) always rejected when using OLS and ACF-L. On the contrary, we often fail to reject the hypothesis of constant returns to scale when we use WOOL and WOOL-LP. One interesting finding is that ACF, OPLP-GMM and (to less extent) the OPLP-NLLS tend to reject the null hypothesis of constant return to scale with moment condition (9) but they fail to reject it with moment condition (11). This exercise shows that empirical results can be very sensitive to the type of estimator that is chosen and the moment conditions that is used. Given that there is no clear indication that the hypothesis is rejected more often for a particular proxy variable or capital rule, the main source of heterogeneity in the estimates seems to be due mainly to the choice of estimator.

The differences between the production function coefficients obtained using the different estimators point to the importance of making suitable timing assumptions for the data at hand. The choice of one estimator over another should ideally be guided by the characteristics of the specific industries and countries in terms of timing and dynamic implications of input choices.

For instance, in the presence of large hiring and firing costs (high employment protection), it can be argued that labour is likely to have dynamic implications (pointing to the ACF or ACF-WOOL estimator as the most appropriate choice). If employee training is important, it can additionally be argued that current labour allocations are uncorrelated with the innovation in productivity, since it will take considerable time before a worker has received proper training and enters the workforce. These are the assumptions made by Konings and Vanormelingen (2009), who use Belgian data to investigate the impact of employee training on firm-level productivity. Similarly, depending on the type of capital used (e.g. equipment, buildings, etc.), investments in new capital will be translated into productive capital at different speeds.

While this approach seems intuitively plausible, it will not always be straightforward to make plausible assumptions in empirical practice. Also, if different industries require different timing assumptions, researchers interested in using data for all manufacturing industries would in principle have to investigate timing assumptions separately for each industry and if necessary, apply different estimators for different industries. This seems undesirable, both from a comparative and practical point of view. Moreover, it is not straightforward to test the validity of the assumptions made in the data.

Finally, firms within industries are likely to allocate inputs in different ways. For instance, it seems quite conceivable that firms employing a lot of high-skilled workers that require specific training are faced with a lag between the time labour is allocated and the time the employee actually contributes to productivity. On the other hand, firms that employ mainly low-skilled workers within the same industry might not be faced with this time lag.

4.2 Monotonicity test

All the estimators analysed above are based on the fundamental assumption that there exists a monotonic relationship between the proxy variable and the unobserved (to the econometrician) productivity, that is for any given value of capital (for OP and LP) or capital and labour (for ACF), firms are assumed to choose a higher value of materials, capacity and investments if they observe a higher shock to productivity. It is therefore surprising that LP is, to the best of our knowledge, the only paper that explores whether this assumption actually holds in the data by means of a graphical analysis.

We propose a simple test that consists in assessing whether the value of the estimated productivity does in fact increase for higher values of the proxy variable. To see how this works in practice, consider the OP estimator. After computing the productivity term as given by equation (3), we regress this variable on a third-order polynomial in capital and investment and we then get the estimated productivity for any chosen value of the two regressors. More precisely, we consider five different values of capital (percentile 1, 25, 50, 75 and 99 of the distribution of capital) and, for any of these five values, we compare estimated productivity for five different values of investment (again, percentile 1, 25, 50, 75 and 99 of the distribution of investment). If we find that the estimated productivity at percentile j of the distribution of investment is higher than productivity of the firm at percentile $i < j$, we assume that monotonicity is satisfied for all the firms with levels of investment between percentile i and j. As said, the comparison of productivity is done by keeping the value of capital fixed, first at percentile 1 of its distribution and then at percentile 25, 50, 75 and 99.

Table 6 reports the percentage of firm-observations that, according to our test, satisfies the monotonicity assumption. Across all the empirical specifications, monotonicity is found to hold in only 58 percent of cases. This surprising finding seems to cast some doubt on the validity of an assumption that is fundamental to all of these estimators, at least for the parametric version implemented in this paper. Mean values reported in the last column suggest that the one-step estimators suggested by Wooldridge (2009) seem to perform particularly bad along this dimension. It is nevertheless reassuring to see that the monotonicity assumption generally seems to hold when using materials as proxy variable.

4.3 Other manufacturing sectors

The average point estimates of labour and capital coefficients across the ten industries are reported in Table 7 and 8, respectively[28]. For each estimator, row N indicates the actual number of industries for which the relevant coefficients can be estimated,[29] while the standard deviation measures the dispersion of these coefficients across the industries.

Some of the findings described in Section 4.1 are confirmed. For instance, OPLP-NLLS and OPLP-GMM tend to produce lower point estimates of the labour coefficient compared to OLS. OPLP-GMM results in higher point estimate of capital than OLS. Again, the ACF (and to less extent the ACF-L) produces higher coefficient on labour than OLS, with estimates varying from 0.82 to 1.16. These values seem suspiciously high, thus confirming our doubts on validity of the ACF approach in our sample. There are also new interesting patterns that emerge in these Tables. First, the (average) coefficients for labour estimated in the first step of the OPLP-NLLS and OPLP-GMM are lower when using materials as proxy variable compared to investments and capacity utilization. We speculate that this is due to the fact that there is a stronger correlation between materials and labour, thus reducing the explicative power of the latter when the first is included in the polynomial of the first stage. Second, the point estimates of the capital coefficient seem to be sensitive to the capital rule used when using investment as proxy variable while this does not seem the case with materials and capacity utilization. In particular, the law of motion (16) consistently delivers higher point estimates than the capital rule (4). Finally, there are no major differences between the WOOL and WOOL-LP estimators. These two estimators produce estimates for β_l similar to the OPLP and smaller than OLS while the estimates of β_k are generally smaller than OPLP and OLS. Differently from the results of the Food and Beverages industry, we now find

[28] Results for the different sectors separately are reported in an online appendix, available at `http://www.econ.kuleuven.be/public/n06017/appendix.pdf`

[29] When N is less then 10, it means that the estimators do not converge for some of the industries.

that the null hypothesis of the Hansen test cannot be rejected for most of the specifications estimated with WOOL.

Table 9 reports the proportion of industries for which at least 80 percent of the observations satisfies the monotonicity test proposed in Section 4.2. We use this "admittedly" arbitrary threshold to indicate that the monotonicity assumption holds in our data when using a particular estimator together with a particular proxy variable and capital rule. Given that it is not always possible to compute the relevant parameters of the production function, the percentage reported in Table 9 does not always refer to the proportion out of ten industries.[30] Overall, the figures confirm the findings for the Food Industry in Table 6 above: there is only mild empirical support for the monotonicity assumption with large differences between proxy variables. In fact, while the variable materials produces reasonably satisfactory results, investment performs (not unexpectedly) rather poorly.

4.4 Comparing productivity distributions

Since the primary interest of obtaining a reliable value of firm-level total factor productivity lies in its use as an evaluation tool in empirical research, we present a simple evaluation exercise to compare the resulting productivity distributions obtained using the different estimators. The ESEE data contain data on firm-level export status. In what follows, we will compare the productivity distribution of exporting and non-exporting firms in particular industries using non-parametric techniques. Our approach largely follows that of Cassiman et al. (2010) and Delgado et al. (2002).

Specifically, we test the equality of the productivity distributions for exporters and non-exporters in a particular year (2001, the middle of our sample) using a Kolmogorov-Smirnov test of equality of distributions. The test compares tests the hypothesis that TFP is smaller for exporters than for non-exporters and the inverse hypothesis that TFP is larger for exporters. The combined test reports the largest difference (positive or negative) between the two distributions and calculates an exact p-value associated with this difference. We compute the test statistic for two industries: the Food and Beverages industry (as in previous sections) and the Chemicals and Plastics sector, which is the only sector for which we have achieved convergence for all the estimators. Results are reported in Tables 10 and 11.

[30]For instance, Table 8 shows that it is possible to compute the capital coefficient of ACF-L with moment equation (9) for nine industries.

The tables report the combined test statistic (the largest difference between the distributions) and its exact p-value. Significance levels indicate to what extent reported differences are significant. While the largest difference between the distribution for exporters and non-exporters is always positive, significance levels vary widely between estimators. For the Food and Beverages industry, the differences between the distributions are always significant for the OPLP-GMM and ACF estimators (if convergence was achieved in the estimation), while for the OPLP-NLLS and WOOL estimators, differences are only significant in some cases. If investment is used as the proxy, results seem to be sensitive to the capital rule used.

Results for the chemical sector (reported in Table 11) are less easy to generalize. Significance levels vary a lot between and within estimators. Results for OPLP-GMM and ACF now seem to be sensitive to the moment condition used (lower or insignificant p-values if equation 11 is used). When capacity utilization is used together with the OP capital rule, the difference between the productivity distribution of exporters and non-exporters is insignificant in the majority of cases.

Overall, these differences suggest that the choice of the estimator can potentially affect the results obtained in policy evaluation exercises. Moreover, the heterogeneity of results between the Food and Beverages sector and Chemicals sector points to the importance of making suitable country- and industry-specific timing assumptions.

5 Conclusions

The use of proxy variables to control for unobservables when estimating a production function has become increasingly popular in recent years. This paper reviews the main assumptions underlying these estimators and tests the sensitivity of production function coefficients to the type of estimator and proxy variable used. In the empirical part of the paper, we propose a test that allows researchers to verify the validity of the monotonicity assumption that underlies all estimators. We also perform a simple exercise to evaluate whether there are significant differences between the productivity of exporters and non-exporters for the different estimators used. Several interesting findings emerge from our analysis, some of which could be the focus of future research.

Specifically, our empirical analysis reveals a high degree of heterogeneity between coefficients obtained using different estimators. This heterogeneity is confirmed by a constant returns to scale test, which yields very different results depending on which estimator is used. Similarly, we find that productivity distribution of exporters and non-exporters is found to be statistically different only for some estimators. All the estimators analysed in this paper rely on the fundamental assumption that there is a monotonic relationship between the proxy variable and the unobserved (to the econometrician) productivity. We therefore propose a simple test, which assesses whether the value of estimated productivity does in fact increase for higher values of the proxy variable. Overall, results suggest that monotonicity fails in many cases, and particularly often when investment is used as the proxy variable. Estimators that use material as proxy variable seem to be preferred along this dimension.

We acknowledge that our results provide very little theoretical guidance on which estimator should be preferred over another. Many of the estimators that have been introduced in recent years rely on specific timing assumptions, which cannot be verified by the econometrician (and which might be different for different industries, countries and even firms). Moreover, there is no clear theoretical prior on how high production function coefficients should be in a particular sector. The empirical findings of this paper suggest that whenever possible, researchers should investigate which timing assumptions are the most appropriate ones for the industry and country at hand (even though this is likely to be hard in empirical practice) and that they should investigate to what extent the monotonicity assumption holds for the data and estimator at hand.

Finally, it can be argued that there are many other methodological issues other than the simultaneity bias that affect production function estimations and which remain unaddressed by the existing class of estimators. Specifically, imperfect competition in input markets will violate the scalar unobservable assumption, which is required in order to preserve the invertibility of the productivity shock. This problem is likely to be particularly relevant when materials is used as the proxy variable. Furthermore, recent research has highlighted the presence of multi-product firms in all industrial sectors. Typically, these firms are very large and they can be active in multiple sectors. These issues raise important questions concerning the relevant level of analysis as well as the assumption of perfect competition in input and output markets.

A Appendix

The survey provides data on manufacturing firms with 10 or more employees. The survey setup is such that all firms with more than 200 employees are invited to participate while a representative sample of about 5 percent of firms with 200 or less employees is randomly selected. In 1990, the first year of the panel, 715 firms with more than 200 employees were surveyed, which accounts for 68 percent of all the Spanish firms of this size. Newly established firms have been added every subsequent year to replace the exits due to death and attrition.

We restrict the sample to firms with at least three years of data on all variables required for estimation. The original industrial classification reported in the survey is based on 18 sectors. In this paper we use a classification based on 10 sectors which seems to be a reasonable compromise between homogeneity of the activity and number of observations available to perform the analysis. These 10 sectors are: 1) Food and beverages; 2) Textiles, clothing and shoes; 3) Timber and furniture; 4) Paper and printing; 5) Chemical and plastic products; 6) Metals and minerals; 7) Metal products; 8) Industrial Machinery; 9) Electrical and electronic goods; 10) Vehicles and transport equipment.

All the variables are expressed in terms of 1990 monetary value. Hereafter, we give some details on the variables used in our empirical exercise.

- *Investment.* Value of current investments in equipment goods (excluding buildings, land, and financial assets) deflated by the price index of investment.
- *Capital.* The first estimate is based on book values adjusted to take account of replacement values. Values in the following years are constructed by capitalizing firms' investments in machinery and equipment, using sectorial rates of depreciation. The capital stock does not include buildings. Real values are obtained using a capital price index.
- *Capacity Utilization.* Yearly average rate of utilization of the standard capacity of production reported by the firms.
- *Labour.* Average number of workers during the year. This average is computed considering the number of full-time and part-time permanent workers at the beginning and the end of the year (two part-time workers

are assumed to be equivalent to a full-time worker) and the number of temporary workers during the four quarters of the year.

- *Materials.* Value of intermediate consumption (including raw materials, components, energy, and services) deflated using an industry-specific price index.
- *Output.* Value of produced goods and services computed as sales plus the variation of inventories deflated by industry specific producer price index.
- *Value Added.* Difference between output and materials. Real values are obtained using an industry-specific value added price index.

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Table 1: Sector distribution of firms

Sector	*Number of firms*	*Number of firm-year observations*	*Average number of employees*	*Average value added (€ 1,000)*
Food & beverages	296	2,575	290	16,003
Textiles, clothing & shoes	265	2,159	153	3,992
Timber & furniture	175	1,328	123	3,351
Paper & printing	177	1,548	208	9,961
Chemicals and plastics	273	2,474	267	13,722
Minerals	133	1,243	244	13,146
Ferrous and non-ferrous metals	272	2,410	215	10,428
Industrial machinery	152	1,390	254	9,036
Electrical goods	135	1,201	323	19,604
Transport	154	1,345	1018	40,671
Total	2,032	17,673		

The table lists the distribution of firms and firm-year observations across manufacturing sectors. Number of employees refer to the average number of employees in each year. Value added is defined as output minus material cost. Nominal values are deflated using a value added deflator (available at sector level). Values reported for value added are real values.

Table 2: Summary statistics of key variables

Variable	*Number of observations*	*Mean*	*Standard deviation*	*Minimum*	*Maximum*
ln(Value added)	17,673	14.67	1.89	6.79	21.74
ln(Employment)	17,673	4.52	1.49	1.10	10.11
ln(Capital OP rule)	17,673	14.60	2.31	6.23	21.95
ln(Capital LP rule)	17,673	14.91	2.28	6.76	22.02
ln(Materials)	17,673	15.33	2.04	7.40	22.20
ln(Investment)	17,673	12.46	2.48	3.50	21.48
ln(Capacity Utilization)	17,673	4.39	0.21	1.61	4.61

The table lists summary statistics for the key variables used in the production function estimations. Number of employees refer to the average number of employees in each year. Value added is defined as output minus material cost. Nominal values are deflated using a value added deflator (available at sector-year level). Values reported for value added are real values. Capital is calculated according to the OP or LP capital rule (cfr. Appendix A). Real values are reported, nominal values are deflated using a year-specific capital deflator. Materials, investment and capacity utilization are used as proxy variables in the production function estimations. Real values of materials are obtained using a materials deflator (available at sector-year level). Variables are defined in Appendix A.

Table 3: Labour coefficients: Food and beverages sector

Proxy variable	*Investment*	*Investment*	*Materials*	*Materials*	*Capacity Utilization*	*Capacity Utilization*	
Capital Rule	*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*	
Estimator	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	*mean*
OLS	0.73*	0.81*	0.73*	0.81*	0.73*	0.81*	0.77
OPLP-NLLS (as) Moment Eq. (9)	0.67*	0.70*	0.73*	0.77*	0.68*	0.75*	0.72
OPLP-NLLS (as) Moment Eq. (11)	0.67*	0.70*	0.73*	0.77*	0.68*	0.75*	0.72
OPLP-GMM Moment: Eq. (9)	0.67*	-	0.73*	0.77*	0.68*	0.75*	0.72
OPLP-GMM Moment Eq. (11)	0.67*	-	0.73*	0.77*	0.68*	0.75*	0.72
ACF Moment Eq. (9)	0.78*	-	0.85*	0.85*	0.96*	0.84*	0.85
ACF Moment Eq. (11)	0.71*	-	-	0.68*	0.90*	0.72*	0.75
ACF-L Moment Eq. (9)	0.76*	0.82*	0.77*	0.79*	0.87*	0.82*	0.80
ACF-L Moment Eq. (11)	0.66*	0.76*	-	0.65*	0.63*	0.63*	0.67
WOOL	0.73*	0.78*	0.76*	0.78*	0.74*	0.80*	0.77
WOOL-ACF	2.91*	3.79*	2.35	3.73*	3.58*	24.87	-
WOOL-LP	0.65*	0.70*	0.66*	0.70*	0.66*	0.72*	0.68
mean	0.71	0.75	0.75	0.75	0.78	0.75	0.75

Values reported are labour coefficients, obtained from estimating a value added production function for the Food and beverages sector, using the estimators listed. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. * indicates significance of at least 5 percent. Means are computed for statistically significant coefficients only (the mean does not include estimates for OLS and WOOL-ACF). The number of observations equals 2,575 in the first stage of the estimation procedure and 2,032 in the second stage, for all estimators. If there is only one estimation stage, the number of observations equals 2,032. The only exception is the WOOL-ACF estimator, where we lose one year of data due to the use of variables lagged two time periods as instruments. Here the number of observations drops to 1,612. If no value is reported, this implies no convergence was achieved in the estimation procedure. The WOOL-ACF estimator is omitted in the calculation of the mean, since the coefficients are not intuitively plausible.

Table 4: Capital coefficients: Food and beverages sector

Proxy variable *Capital Rule*	*Investment* *Eq. (16)*	*Investment* *Eq. (4)*	*Materials* *Eq. (16)*	*Materials* *Eq. (4)*	*Capacity Utilization* *Eq. (16)*	*Capacity Utilization* *Eq. (4)*	
Estimator	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	Coeff.	*mean*
OLS	0.38*	0.32*	0.38*	0.32*	0.38*	0.32*	0.35
OPLP-NLLS (as) Moment Eq. (9)	0.38*	0.08*	0.34*	0.39*	0.44*	0.37*	0.33
OPLP-NLLS (as) Moment Eq. (11)	0.33*	0.06*	0.37*	0.29*	0.26*	0.27*	0.26
OPLP-GMM Moment: Eq. (9)	0.46*	-	0.43*	0.40*	0.47*	0.43*	0.43
OPLP-GMM Moment Eq. (11)	0.44*	-	0.44*	0.42*	0.45*	0.42*	0.43
ACF Moment Eq. (9)	0.39*	-	0.37*	0.36*	0.30*	0.34*	0.35
ACF Moment Eq. (11)	0.42*	-	-	0.48*	0.31*	0.41*	0.40
ACF-L Moment Eq. (9)	0.40*	0.33*	0.41*	0.41*	0.35*	0.36*	0.38
ACF-L Moment Eq. (11)	0.45*	0.37*	-	0.50*	0.47*	0.47*	0.45
WOOL	0.28*	0.07	0.29*	0.21*	0.28*	0.22*	0.25
WOOL-ACF	0.10	-0.36	0.09	0.16	0.02	-0.17	-
WOOL-LP	0.27*	0.82	0.29*	0.34*	0.28*	0.37*	0.31
mean	0.38	0.21	0.37	0.38	0.36	0.37	0.36

Values reported are capital coefficients, obtained from estimating a value added production function for the Food and beverages sector, using the estimators listed. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. * indicates significance of at least 5 percent. Means are computed for statistically significant coefficients only (the mean does not include estimates for OLS and WOOL-ACF). The number of observations equals 2,575 in the first stage of the estimation procedure and 2,032 in the second stage, for all estimators. If there is only one estimation stage, the number of observations equals 2,032. The only exception is the WOOL-ACF estimator, where we lose one year of data due to the use of variables lagged two time periods as instruments. Here the number of observations drops to 1,612. If no value is reported, this implies no convergence was achieved in the estimation procedure. The WOOL-ACF estimator is omitted in the calculation of the mean, since the coefficients are not intuitively plausible.

Table 5: Constant returns to scale test: Food and beverages sector

Proxy variable	*Investment*	*Investment*	*Materials*	*Materials*	*Capacity Utilization*	*Capacity Utilization*
Capital Rule	*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*
Estimator	p-value	p-value	p-value	p-value	p-value	p-value
OLS	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
OPLP-NLLS (as) Moment Eq. (9)	0.02*	0.00*	0.00*	0.00*	0.00*	0.00*
OPLP-NLLS (as) Moment Eq. (11)	0.97	0.00*	0.00*	0.05*	0.05*	0.44
OPLP-GMM Moment: Eq. (9)	0.00*	-	0.00*	0.00*	0.06	0.04*
OPLP-GMM Moment Eq. (11)	0.06	-	0.24	0.14	0.31	0.19
ACF Moment Eq. (9)	0.00*	-	0.00*	0.00*	0.00*	0.36
ACF Moment Eq. (11)	0.30	-	-	0.00*	0.01*	0.57
ACF-L Moment Eq. (9)	0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
ACF-L Moment Eq. (11)	0.00*	0.00*	-	0.00*	0.00*	0.00*
WOOL	0.86	0.14	0.38	0.88	0.68	0.70
WOOL-ACF	-	-	-	-	-	-
WOOL-LP	0.25	0.60	0.51	0.69	0.37	0.23

Values reported are p-values, obtained from a constant returns to scale test, using the estimated production function coefficients for the Food and beverages sector, reported in Tables 3 and 4. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. * indicates significance of at least 5 percent. If no value is reported, this implies no convergence was achieved in the estimation procedure. Results for the Wooldridge-ACF estimator are omitted since the labour and capital coefficients obtained are not intuitively plausible (cfr. Tables 3-4).

Table 6: Monotonicity test: Food and beverages sector

Proxy variable *Capital Rule*	*Investment* *Eq. (16)*	*Investment* *Eq. (4)*	*Materials* *Eq. (16)*	*Materials* *Eq. (4)*	*Capacity Utilization* *Eq. (16)*	*Capacity Utilization* *Eq. (4)*	
Estimator	Percentage	Percentage	Percentage	Percentage	Percentage	Percentage	*mean*
OPLP-NLLS (as) Moment Eq. (9)	50	80*	75	90*	35	35	61
OPLP-NLLS (as) Moment Eq. (11)	50	80*	75	90*	35	35	61
OPLP-GMM Moment: Eq. (9)	50	-	75	90*	35	35	57
OPLP-GMM Moment Eq. (11)	50	-	75	90*	35	35	57
ACF Moment Eq. (9)	53	-	66	82*	69	70	68
ACF Moment Eq. (11)	53	-	-	82*	69	70	69
ACF-L Moment Eq. (9)	53	76	66	82*	69	70	69
ACF-L Moment Eq. (11)	53	76	-	82*	69	70	70
WOOL	55	35	5	5	5	25	22
WOOL-ACF	-	-	-	-	-	-	-
WOOL-LP	35	45	55	80*	30	25	45
mean	50	65	62	77	45	47	58

Values reported represent the percentage of observations for which the monotonicity test is passed. The details of the monotonicity test are explained in section 4.2.1. If the test is passed for at least 80 percent of cases, monotonicity is assumed to hold for the data and estimator concerned. This is indicated by a * in the table. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text.If no value is reported, this implies no convergence was achieved in the estimation procedure. Results for the Wooldridge-ACF estimator are omitted since the labour and capital coefficients obtained are not intuitively plausible (cfr. Tables 3-4).

Table 7: Labour coefficients: Comparison across sectors

Proxy variable		*Investment*	*Investment*	*Materials*	*Materials*	*Capacity Utilization*	*Capacity Utilization*
Capital Rule		*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*	*Eq. (16)*	*Eq. (4)*
Estimator		*Values*	*Values*	*Values*	*Values*	*Values*	*Values*
OLS	*Mean*	0.84	0.87	0.84	0.87	0.84	0.87
	Stdev.	0.09	0.08	0.09	0.08	0.09	0.08
	N	10	10	10	10	10	10
OPLP-NLLS (as) Moment Eq. (9)	*Mean*	0.80	0.82	0.66	0.67	0.81	0.85
	Stdev.	0.10	0.10	0.09	0.09	0.10	0.09
	N	10	10	10	10	10	10
OPLP-NLLS (as) Moment Eq. (11)	*Mean*	0.80	0.82	0.66	0.67	0.81	0.85
	Stdev.	0.10	0.10	0.09	0.09	0.10	0.09
	N	10	10	10	10	10	10
OPLP-GMM Moment: Eq. (9)	*Mean*	0.80	0.86	0.64	0.69	0.80	0.88
	Stdev.	0.10	0.09	0.08	0.09	0.10	0.08
	N	10	5	9	8	9	8
OPLP-GMM Moment Eq. (11)	*Mean*	0.79	0.90	0.66	0.67	0.81	0.85
	Stdev.	0.10	0.03	0.09	0.09	0.10	0.09
	N	7	4	9	10	10	9
ACF Moment Eq. (9)	*Mean*	0.82	0.85	0.97	0.96	0.88	0.85
	Stdev.	0.12	0.09	0.14	0.17	0.13	0.09
	N	8	7	10	10	9	10
ACF Moment Eq. (11)	*Mean*	0.97	1.16	0.96	0.89	0.82	0.86
	Stdev.	0.72	0.86	0.33	0.26	0.24	0.29
	N	9	9	8	10	8	10
ACF-L Moment Eq. (9)	*Mean*	0.82	0.88	0.88	0.91	0.85	0.86
	Stdev.	0.11	0.09	0.08	0.11	0.09	0.09
	N	9	9	10	10	10	10
ACF-L Moment Eq. (11)	*Mean*	0.80	0.88	0.84	0.87	0.81	0.83
	Stdev.	0.15	0.15	0.18	0.17	0.16	0.16
	N	9	9	9	10	10	10
WOOL	*Mean*	0.80	0.83	0.65	0.67	0.79	0.84
	Stdev.	0.11	0.10	0.12	0.10	0.09	0.10
	N	10	10	10	10	9	9
WOOL-ACF	*Mean*	3.24	2.85	2.12	2.69	3.67	4.98
	Stdev.	0.91	0.80	0.68	0.80	2.32	7.04
	N	10	10	10	10	9	10
WOOL-LP	*Mean*	0.79	0.81	0.61	0.64	0.79	0.82
	Stdev.	0.12	0.11	0.13	0.10	0.12	0.11
	N	10	10	10	10	10	10

Values reported are obtained from estimating a value added production function at the sector level, using the estimators listed. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. The number of observations equals 2,575 in the first stage of the estimation procedure and 2,032 in the second stage, for all estimators. If there is only one estimation stage, the number of observations equals 2,032. The only exception is the WOOL-ACF estimator, where we lose one year of data due to the use of variables lagged two time periods as instruments. Here the number of observations drops to 1,612. For each estimator, we report the number of observations the mean labour coefficient across the different sectors and its standard deviation. If the number of observations is smaller than 10, this implies that convergence was not achieved for one or more industries.

Table 8: Capital coefficients: Comparison across sectors

Proxy variable / *Capital Rule*		*Investment Eq. (16)*	*Investment Eq. (4)*	*Materials Eq. (16)*	*Materials Eq. (4)*	*Capacity Utilization Eq. (16)*	*Capacity Utilization Eq. (4)*
Estimator		*Values*	*Values*	*Values*	*Values*	*Values*	*Values*
OLS	*Mean*	0.24	0.21	0.24	0.21	0.24	0.21
	Stdev.	0.08	0.07	0.08	0.07	0.08	0.07
	N	10	10	10	10	10	10
OPLP-NLLS (as) Moment Eq. (9)	*Mean*	0.26	0.20	0.20	0.15	0.25	0.22
	Stdev.	0.09	0.09	0.07	0.09	0.09	0.07
	N	10	10	10	10	10	10
OPLP-NLLS (as) Moment Eq. (11)	*Mean*	0.19	0.08	0.17	0.12	0.19	0.19
	Stdev.	0.08	0.06	0.08	0.09	0.05	0.09
	N	10	10	10	10	10	10
OPLP-GMM Moment: Eq. (9)	*Mean*	0.27	0.21	0.38	0.33	0.27	0.23
	Stdev.	0.11	0.07	0.06	0.09	0.11	0.11
	N	10	5	9	8	9	8
OPLP-GMM Moment Eq. (11)	*Mean*	0.29	0.09	0.29	0.31	0.23	0.24
	Stdev.	0.10	0.21	0.21	0.20	0.15	0.14
	N	7	4	9	10	10	9
ACF Moment Eq. (9)	*Mean*	0.28	0.23	0.21	0.20	0.24	0.25
	Stdev.	0.10	0.07	0.11	0.12	0.07	0.09
	N	8	7	10	10	9	10
ACF Moment Eq. (11)	*Mean*	0.25	0.14	0.17	0.25	0.27	0.28
	Stdev.	0.21	0.23	0.22	0.20	0.17	0.16
	N	9	9	8	10	8	10
ACF-L Moment Eq. (9)	*Mean*	0.27	0.22	0.25	0.23	0.26	0.24
	Stdev.	0.09	0.07	0.10	0.11	0.08	0.09
	N	9	9	10	10	10	10
ACF-L Moment Eq. (11)	*Mean*	0.28	0.22	0.22	0.25	0.26	0.26
	Stdev.	0.12	0.12	0.18	0.16	0.15	0.14
	N	9	9	9	10	10	10
WOOL	*Mean*	0.18	0.08	0.15	0.10	0.20	0.19
	Stdev.	0.06	0.11	0.06	0.09	0.05	0.09
	N	10	10	10	10	9	9
WOOL-ACF	*Mean*	-0.12	0.15	-0.04	0.08	-0.14	0.06
	Stdev.	0.18	1.32	0.14	0.14	0.43	0.14
	N	10	10	9	10	10	9
WOOL-LP	*Mean*	0.17	0.54	0.17	0.14	0.18	0.24
	Stdev.	0.06	0.44	0.07	0.10	0.05	0.09
	N	10	10	10	10	10	10

Values reported are obtained from estimating a value added production function at the sector level, using the estimators listed. Columns report results for different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. The number of observations equals 2,575 in the first stage of the estimation procedure and 2,032 in the second stage, for all estimators. If there is only one estimation stage, the number of observations equals 2,032. The only exception is the WOOL-ACF estimator, where we lose one year of data due to the use of variables lagged two time periods as instruments. Here the number of observations drops to 1,612. For each estimator, we report the number of observations the mean capital coefficient across the different sectors and its standard deviation. If the number of observations is smaller than 10, this implies that convergence was not achieved for one or more industries.

Table 10: TFP distribution of exporters versus non-exporters in 2001: Food and beverages

Proxy variable / *Capital Rule* / *Estimator*	Statistic	*Investment Eq. (16)*	*Investment Eq. (4)*	*Materials Eq. (16)*	*Materials Eq. (4)*	*Capacity Utilization Eq. (16)*	*Capacity Utilization Eq. (4)*
OLS	D	0.25**	0.24**	0.25**	0.24**	0.25**	0.24**
	exact p	0.01	0.01	0.01	0.01	0.01	0.01
OPLP-NLLS (as) Moment Eq. (9)	D	0.17	0.33***	0.18	0.31***	0.28***	0.24**
	exact p	0.16	0.00	0.12	0.00	0.00	0.01
OPLP-NLLS (as) Moment Eq. (11)	D	0.12	0.34***	0.21**	0.18	0.17	0.11
	exact p	0.53	0.00	0.04	0.10	0.15	0.59
OPLP-GMM Moment: Eq. (9)	D	0.31***	-	0.32***	0.30***	0.34***	0.32***
	exact p	0.00		0.00	0.00	0.00	0.00
OPLP-GMM Moment Eq. (11)	D	0.30***	-	0.33***	0.32***	0.31***	0.31***
	exact p	0.00		0.00	0.00	0.00	0.00
ACF Moment Eq. (9)	D	0.29***	-	0.32***	0.33***	0.36***	0.31***
	exact p	0.00		0.00	0.00	0.00	0.00
ACF Moment Eq. (11)	D	0.29***	-	-	0.34***	0.30***	0.28***
	exact p	0.00			0.00	0.00	0.00
ACF-L Moment Eq. (9)	D	0.29***	0.27***	0.33***	0.32***	0.32***	0.30***
	exact p	0.00	0.00	0.00	0.00	0.00	0.00
ACF-L Moment Eq. (11)	D	0.30***	0.24**	-	0.33***	0.31***	0.28***
	exact p	0.00	0.01		0.00	0.00	0.00
WOOL	D	0.11	0.31***	0.14	0.13	0.11	0.11
	exact p	0.65	0.00	0.32	0.42	0.60	0.64
WOOL-ACF	D	-	-	-	-	-	-
	exact p						
WOOL-LP	D	0.20*	0.48***	0.16	0.14	0.17	0.21**
	exact p	0.05	0.00	0.21	0.33	0.15	0.04

Values reported are obtained using a Kolmogorov-Smirnov test for equality of the distributions for exporting and non-exporting firms. The number of observations equals 170. The D-values indicate the largest difference between the distribution for exporters and non-exporters (combining positive and negative differences, while the exact p-value indicates whether the distributions are significantly different between exporters and non-exporters. Columns report results for TFP estimated using different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. If no value is reported, this implies no convergence was achieved in the estimation procedure. The WOOL-ACF estimator is omitted as well, since the coefficients are not intuitively plausible. Significance levels (based on the exact p-value reported): *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 11: TFP distribution of exporters versus non-exporters in 2001: Chemicals

Proxy variable / *Capital Rule* / *Estimator*	*Statistic*	*Investment Eq. (16)*	*Investment Eq. (4)*	*Materials Eq. (16)*	*Materials Eq. (4)*	*Capacity Utilization Eq. (16)*	*Capacity Utilization Eq. (4)*
OLS	D	0.22*	0.19	0.22*	0.19	0.22*	0.19
	exact p	0.07	0.15	0.07	0.15	0.07	0.15
OPLP-NLLS (as) Moment Eq. (9)	D	0.22*	0.21*	0.49***	0.50***	0.22*	0.19
	exact p	0.05	0.07	0.00	0.00	0.05	0.15
OPLP-NLLS (as) Moment Eq. (11)	D	0.32***	0.36***	0.51***	0.53***	0.31***	0.20
	exact p	0.00	0.00	0.00	0.00	0.00	0.12
OPLP-GMM Moment: Eq. (9)	D	0.22*	0.21*	0.22*	0.19	0.22*	0.20
	exact p	0.05	0.07	0.07	0.13	0.07	0.12
OPLP-GMM Moment Eq. (11)	D	0.28**	0.22*	0.58***	0.55***	0.51***	0.33***
	exact p	0.01	0.06	0.00	0.00	0.00	0.00
ACF Moment Eq. (9)	D	0.22*	0.21*	0.19	0.20	0.22*	0.19
	exact p	0.05	0.08	0.16	0.10	0.07	0.13
ACF Moment Eq. (11)	D	0.27**	0.28**	0.37***	0.32***	0.31***	0.25**
	exact p	0.01	0.01	0.00	0.00	0.00	0.02
ACF-L Moment Eq. (9)	D	0.23**	0.23*	0.19	0.32**	0.22*	0.19
	exact p	0.04	0.05	0.13	0.04	0.07	0.13
ACF-L Moment Eq. (11)	D	0.26**	0.27**	0.56***	0.39***	0.32***	0.25**
	exact p	0.02	0.01	0.00	0.00	0.00	0.02
WOOL	D	0.37***	0.27**	0.50***	0.55***	0.33***	0.25**
	exact p	0.00	0.01	0.00	0.00	0.00	0.02
WOOL-ACF	D	-	-	-	-	-	-
	exact p						
WOOL-LP	D	0.36***	0.19	0.52***	0.53***	0.33***	0.13
	exact p	0.00	0.16	0.00	0.00	0.00	0.60

Values reported are obtained using a Kolmogorov-Smirnov test for equality of the distributions for exporting and non-exporting firms. The number of observations equals 180. The D-values indicate the largest difference between the distribution for exporters and non-exporters (combining positive and negative differences, while the exact p-value indicates whether the distributions are significantly different between exporters and non-exporters. Columns report results for TFP estimated using different proxy variables and different capital rules (cfr. Equations (4) and (16) in the text). Different moment conditions are used for some GMM estimators, cfr. Equations (9) and (11) in the text. If no value is reported, this implies no convergence was achieved in the estimation procedure. The WOOL-ACF estimator is omitted as well, since the coefficients are not intuitively plausible. Significance levels (based on the exact p-value reported): *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.