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Total Factor Productivity Estimation: A Practical Review*

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Abstract

This paper aims to provide empirical researchers with an overview of the methodological issues that arise when estimating total factor productivity at the establishment level, as well as of the existing (parametric and semiparametric) techniques designed to overcome them. Apart from the well-known simultaneity and selection bias; attention is given to methodological issues that have emerged more recently and that are related to the use of deflated values of inputs and outputs (as opposed to quantities) in estimating productivity at the firm level, as well as to the endogeneity of product choice. Using data on single-product firms active in the Belgian food and beverages sector, I illustrate the biases introduced in traditional TFP estimates and discuss the performance of a number of alternative estimators that have been proposed in the literature.

Keywords: Total factor productivity; Imperfect competition; Endogenous product choice; Semiparametric estimator; Demand. JEL Classification: C13; C14; D24, D40.

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1 Introduction

While the origins of total factor productivity analysis can be traced back to the seminal paper by Solow (Solow, 1957); recent years have seen a surge in both theoretical and empirical studies on total factor productivity (TFP). This renewed interest has been driven both by the increasing availability of firm-level data, allowing for estimation of TFP at the level of the individual establishment (Bartelsman and Doms, 2000); as well as by a number of methodological improvements that have emerged from the literature since the mid-1990s (Ackerberg, Benkard, Berry and Pakes, 2007, henceforth ABBP).

Typically, establishment-level productivity studies assume output (usually measured as deflated sales or value added) to be a function of the inputs the firm employs and its productivity (Katayama, Lu and Tybout, 2005). The measure of TFP obtained as the residual in this functional relationship is then used to evaluate the impact of various policy measures, such as the extent of foreign ownership (eg. Smarzynska Javorcik, 2004), trade liberalization (eg. Pavcnik, 2002; Amiti and Konings, 2007; De Loecker, 2007) and antidumping protection (eg. Konings, 2008).

However, several methodological issues emerge when TFP is estimated using traditional methods, i.e. by applying Ordinary Least Squares (OLS) to a balanced panel of (continuing) firms. First, since productivity and input choices are likely to be correlated, OLS estimation of firm-level production functions introduces a simultaneity or endogeneity problem. Moreover, by using a balanced panel, no allowance is made for entry and exit, resulting in a selection bias. Although the simultaneity and selection bias are well-known[1]; several other methodological issues have emerged more recently. Specifically, the typical practice of proxying for firm-level prices using industry-level deflators has been challenged (see for instance Katayama et al., 2005). Moreover, Bernard, Redding and Schott (2005) note that firms' product choices are likely to be related to their productivity.

In response to these methodological issues, several (parametric and semi-parametric) estimators have been proposed in the literature. However, traditional estimators used to overcome endogeneity issues (i.e. fixed effects, instrumental variables and Generalized Method of Moments or GMM) have not proved satisfactory for the case of production functions. Likely causes

[1] They have been documented at least since Marschak and Andrews (1944) and Wedervang (1965) respectively.

for these estimators' poor performance are related to their underlying assumptions. Therefore, a number of semiparametric alternatives have been proposed. Both Olley and Pakes (1996, henceforth OP) and Levinsohn and Petrin (2003, henceforth LP) have developed a semiparametric estimator that addresses the simultaneity bias (and the selection bias in the case of the OP estimator). Several extensions to their model have already been introduced (eg. De Loecker, 2007).

The present paper aims to provide empirical researchers with an overview of the methodological issues that arise when estimating TFP at the establishment level, as well as of the existing techniques designed to overcome them. Using data on single-product firms active in the Belgian food and beverages sector, I illustrate the biases introduced in traditional TFP estimates and discuss the performance of a number of alternative estimators that have been used in the literature. The food and beverages industry in Belgium presents an interesting case, since the sector underwent significant restructuring at the end of the 1990s following the dioxin crisis[2].

The production function coefficients obtained using various estimation techniques (i.e. OLS, fixed effects, GMM, Olley-Pakes, Levinsohn-Petrin and De Loecker) are generally in line with theoretical predictions. Aggregate productivity growth in the food and beverages industry increases significantly after 1999, consistent with the period of restructuring and increasing investments in the sector in response to the dioxin scandal (VRWB, 2003). Decomposing aggregate productivity into a within productivity component and a reallocation share on the basis of firms' turnover shares shows that this increase is mainly due to the average firm becoming more productive; while reallocation of market shares explains only a minor part. Applying the same decomposition using employment rather than output shares yields similar results.

The rest of the paper is structured as follows. Section 2 provides an overview of the methodological issues arising when estimating firm-level TFP. In section 3, several estimation methods are reviewed, with specific attention for their advantages and drawbacks. Section 4 illustrates the different methodologies for the Belgian food and beverages industry (NACE 15). Section 5 concludes.

[2]The Economist (1999). Excessive concentrations of dioxin were found in eggs, chicken, pork and milk, caused by contaminated animal food.

Given the vast amount of papers that continue to emerge in this field, a number of choices have to be made at the outset. First, since primary interest is in consistent estimation of TFP, attention will mostly be limited to recent papers, i.e. from 1990 onwards. Second, only parametric and semiparametric estimators applied to TFP estimation will be discussed here. Van Biesebroeck (2007) provides an excellent review of several non-parametric methods (specifically, index numbers and data envelopment analysis)[3] used to estimate firm-level productivity. Finally, given the multitude of papers dealing with the impact of some policy measure on TFP, it is beyond the scope of the present paper to provide a complete review of all the empirical work done in this area. Selection of which references to include is therefore based on their methodological and econometric contributions to the field.

2 Total factor productivity: Methodological issues

2.1 Some preliminaries on the production function

I start by assuming that production takes the form of a Cobb-Douglas production function. However, as shown by ABBP (2007); estimation methods discussed in the next section carry over to other types of production functions, provided some basic requirements are met[4]. Specifically, the production function looks as follows:

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

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

While Y_{it}, K_{it}, L_{it} and M_{it} are all observed by the econometrician (although usually in value terms rather than in quantities, see below), A_{it} is unobservable to the researcher. Taking natural logs of (1) results in a linear

[3] Van Biesebroeck (2007) compares the robustness of five commonly used techniques to estimate TFP: index numbers, data envelopment analysis, stochastic frontiers, GMM and semiparametric estimation; to the presence of measurement error and to differences in production technology.

[4] Variable inputs need to have positive cross-partials with productivity and the value of the firm has to be increasing in the amount of fixed inputs used (ABBP, 2007).

production function,

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it}$$

where lower-case letters refer to natural logarithms and

$$\ln(A_{it}) = \beta_0 + \varepsilon_{it}$$

.

While β_0 measures the mean efficiency level across firms and over time; ε_{it} is the time- and producer-specific deviation from that mean, which can then be further decomposed into an observable (or at least predictable) and unobservable component. This results in the following equation, which will serve as the starting point for the rest of this and the next section:

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

where ω_{it} represents firm-level productivity[5] and u_{it}^q is an i.i.d. component, representing unexpected deviations from the mean due to measurement error, unexpected delays or other external circumstances.

Typically, empirical researchers estimate (2) and solve for ω_{it}. Estimated productivity can then be calculated as follows:

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} \tag{3}$$

and productivity in levels can be obtained as the exponential of $\hat{\omega}_{it}$, i.e. $\hat{\Omega}_{it} = \exp(\hat{\omega}_{it})$. The productivity measure resulting from (3) 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 $\hat{\Omega}_{it}$.

Weights used to aggregate firm-level TFP can be either firm-level output shares, as in OP; or employment shares, as in De Loecker and Konings (2006). As will be illustrated in section 4, normalized industry productivity can then be further decomposed into an unweighted average and a (cross-sectional) sample covariance term. While differences in the unweighted average over time refer to within-firm changes in TFP; changes in the sample covariance term signal reallocation of market shares as the driver of productivity shifts (Olley and Pakes, 1996; De Loecker and Konings, 2006).

[5] The productivity term is identified through the assumption that ω_{it} is a state variable in the firm's decision problem (i.e. it is a determinant of both firm selection and input demand decisions), while u_{it}^q is either measurement error or a non-predictable productivity shock (Olley and Pakes, 1996).

In what follows, it will be shown that estimating (2) using OLS leads to biased productivity estimates, caused by the endogeneity of input choices and selection bias. Moreover, in the presence of imperfect competition in output and/or input markets, an omitted variable bias will arise in standard TFP estimation if data on physical inputs and output and their corresponding firm-level prices are unavailable. Finally, if firms produce multiple products, potentially differing in their production technology; failure to estimate the production function at the appropriate product level, rather than at the firm level, will also introduce a bias in standard TFP measures. I will discuss each of these problems in turn.

2.2 Endogeneity of attrition or selection bias

Traditionally, entry and exit of firms is accounted for in TFP estimation by constructing a balanced panel; i.e. by omitting all firms that enter or exit over the sample period (Olley and Pakes, 1996). However, several theoretical models (eg. Jovanovic, 1982; Hopenhayn, 1992) predict that the growth and exit of firms is motivated to a large extent by productivity differences at the firm level. Empirically, Fariñas and Ruano (2005) find, for a sample of Spanish manufacturing firms, that entry and exit decisions are systematically related to differences in productivity. They show that firms' exit patterns reflect initial productivity differences, leading to the prediction that higher productivity will lower the exit probability at the firm level.

Moreover, Dunne et al. (1988) report exit rates in excess of 30 percent between two census years in US manufacturing and a strong correlation between entry and exit rates in the data. Since low productivity firms have a stronger tendency to exit than their more productive counterparts, omitting all firms subject to entry or exit is likely to lead to biased results. If firms have some knowledge about their productivity level ω_{it} prior to their exit, this will generate correlation between ε_{it} and the fixed input capital, conditional on being in the data set (ABBP, 2007). This correlation has its origin in the fact that firms with a higher capital supply will (ceteris paribus) be able to withstand lower ω_{it} without exiting.

In sum, the selection bias or "endogeneity of attrition"- problem will generate a negative correlation between ε_{it} and K_{it}, causing the capital coefficient to be biased downwards in a balanced sample (i.e. not taking entry and exit into account). While this selection problem has been discussed in the literature at least since the work of Wedervang (1965), the estimation algorithm introduced by Olley and Pakes (1996) was the first to take it explicitly[6] into account.

2.3 Endogeneity of input choice or simultaneity bias

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. This "endogeneity of inputs" or simultaneity bias is defined as the correlation between the level of inputs chosen and unobserved productivity shocks (De Loecker, 2007).

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). Hence, if there is serial correlation in ω_{it}, a positive productivity shock will lead to increased variable input usage; i.e. $E\left(x_{it}\omega_{it}\right) > 0$, where $x_{it} = (l_{it}, m_{it})$; introducing an upward bias in the input coefficients for labor and materials (De Loecker, 2007). 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 labor 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 labor and capital (which is the most likely setup).

Traditional methods to deal with heterogeneity and endogeneity issues include fixed effects and instrumental variables estimation (Wooldridge, 2005). However, as I will discuss below, both alternatives to OLS are plagued by a number of problems. Both the estimation algorithm introduced by Olley and Pakes (1996) and Levinsohn and Petrin (2003) provide a more adequate solution to the simultaneity problem discussed here.

[6] It is possible to correct implicitly for the selection bias by using an unbalanced panel of firms. But, as will be shown in section 3, Olley and Pakes (1996) introduce an additional (explicit) correction in their estimation algorithm, i.e. they take the firm-level survival probability into account.

2.4 Omitted output price bias

In the absence of information on firm-level prices, which are typically unavailable to the researcher, industry-level price indices are usually applied to deflate firm-level sales (and hence obtain a measure of the firm's output) in traditional production function estimates (De Loecker, 2007). However, if firm-level price variation is correlated with input choice; this will result in biased input coefficients. The problem can be illustrated as follows. Replacing output in quantities by deflated sales in (2) results in the following model:

$$\begin{aligned} \widetilde{r}_{it} &= p_{it} + y_{it} - \overline{p}_{it} \\ &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + (p_{it} - \overline{p}_{it}) + \omega_{it} + u_{it}^q \end{aligned} \tag{4}$$

where $\widetilde{r}_{it}$ represents deflated sales, p_{it} are firm-level prices and $\overline{p}_{it}$ is the industry-level price deflator, all in logarithmic form. For now, inputs are still assumed to be available in quantities. From (4) it is clear that if input choice is correlated with unobserved firm-level price differences, i.e. $E\left(x_{it}\left(p_{it} - \overline{p}_{it}\right)\right) \neq 0$, where $x_{it} = (l_{it}, m_{it}, k_{it})$; a bias is introduced in the input coefficients.

Assuming inputs and output are positively correlated and output and price are negatively correlated (as in a standard demand and supply framework); the correlation between (variable) inputs and firm-level prices will be negative; resulting in a negative bias for the coefficients on labor and materials (De Loecker, 2007). Hence, the bias resulting from using industry-level price deflators rather than firm-level prices to deflate sales, will generally be opposite to the bias introduced by simultaneity of input choice and productivity discussed in the previous section.

Since the omitted output price bias will only arise if industry-level price deflators are used and if firm-level prices deviate from these deflators (i.e. in the presence of imperfect competition), it can be avoided by using quantities of output rather than deflated sales. However, since this requires information on actual firm level prices, it is a very rare setup. Exceptions include Dunne and Roberts (1992), Eslava, Haltiwanger, Kugler and Kugler (2004), Foster, Haltiwanger and Syverson (2008), Jaumandreu and Mairesse (2004) and Mairesse and Jaumandreu (2005). Alternatively, it is possible (in the absence of information on prices) to introduce demand for output into the system and solve for firm-level prices[7], as suggested by Klette and Griliches

[7] Ornaghi (2006) criticizes this approach however, see section 3 below.

(1996), Levinsohn and Melitz (2002) and, in the context of the Olley-Pakes semiparametric estimator, De Loecker (2007). The specifics of the latter estimation algorithm will be discussed in section 3.

2.5 Omitted input price bias

In the presence of imperfect competition in input markets, input prices are likely to be firm-specific. However, since input prices (like output prices) are typically unavailable, quantities of inputs are usually proxied by deflated values of inputs for capital and materials (the amount of labor used tends to be available in annual accounts data commonly used to estimate production function relationships). Assuming that quantities of output are given, this leads to the following relationship:

$$y_{it} = \beta_0 + \beta_k \widetilde{k}_{it} + \beta_l l_{it} + \beta_m \widetilde{m}_{it} + \omega_{it} + u^q_{it}$$

$$\begin{aligned} y_{it} &= \beta_0 + \beta_k \left(k_{it} + p^k_{it} - \overline{p}^k_{it}\right) + \beta_l l_{it} \\ &+ \beta_m \left(m_{it} + p^m_{it} - \overline{p}^m_{it}\right) + \omega_{it} + u^q_{it} \end{aligned} \tag{5}$$

where $\widetilde{k}_{it}$ and $\widetilde{m}_{it}$ are deflated values of capital and material inputs respectively, p^k_{it} and p^m_{it} represent firm-level prices of these inputs and $\overline{p}^k_{it}$ and $\overline{p}^m_{it}$ refer to their industry-level price indices. From (5) it is clear that in the presence of unobserved firm-level input price differences, coefficients on $\widetilde{k}_{it}$ and $\widetilde{m}_{it}$ will be biased.

De Loecker (2007) argues that if imperfect output markets are treated explicitly, this can partly take care of the omitted input price bias, to the extent that higher input prices are reflected in higher output prices; which in turn depends on the relevant firm-level mark-up. However, Levinsohn and Melitz (2002) argue that even with a competitive factor market, adjustment costs will lead to differences in the shadow price of the input index across firms, induced by differences in current levels of the quasi-fixed factors (capital). Katayama et al. (2005) similarly argue that factor prices are important to take into account in TFP estimation procedures.

Similar to the situation of imperfect competition in output markets, a number of studies are able to exploit information on input prices and quantities to resolve the omitted price bias, examples include Eslava et al. (2004) and Ornaghi (2006). A formal solution for the bias induced by firm-specific input prices has yet to be introduced.

2.6 Endogeneity of the product mix (multi-product firms)

Bernard, Redding and Schott (2005, henceforth BRS) argue that firms' decisions on which goods to produce, are typically made at a more disaggregated level than is recorded in manufacturing data sets (either using census data or annual accounts data). If firms produce multiple products within the same industry and if these products differ in their production technology or in the demand they face, this will lead to biased TFP estimates, since the production function assumes identical production techniques and final demand (through the use of common output price deflators) across products manufactured by a single firm.

BRS (2006b) have examined the pervasiveness and determinants of product switching among US manufacturing firms for the period 1972-1992. They find that two-thirds of firms alter their mix of five-digit SIC codes every five years and they further demonstrate that product adding and dropping by surviving firms accounts for nearly one-third of the aggregate growth in real US manufacturing output between 1992 and 1997.

In principle, consistent estimation of TFP in the presence of multi-product firms requires information on the product mix, product-level output, inputs, as well as prices. Given these high requirements in terms of data, BRS (2005) suggest several (partial) solutions to circumvent the bias introduced by multi-product firms. First, in the absence of information on inputs and outputs at the product level, it is possible to sort firms into groups that make a single product, which will eliminate the bias introduced by endogenous product choice. Alternatively, if the researcher has knowledge of the number and type of products produced by each firm, consistent estimates of productivity can be obtained by allowing the parameters of the production technology to vary across firms making different products. De Loecker (2007) is among the first to take the number of products as well as product-specific demand into account when estimating TFP for the Belgian textiles sector. However, his estimation procedure provides only a partial solution to the bias introduced by endogenous product choice (cfr. section 3).

2.7 Summary of methodological issues

Traditional productivity estimates, obtained as the residual from a balanced OLS regression of deflated output on deflated inputs and a constant, are plagued by a number of econometric and specification issues. Table 1 provides an overview.

First, given the prevalence of entry and exit in manufacturing populations, the use of a balanced panel introduces a selection bias in the sample, causing the capital coefficient to be biased downward. Second, if firms have some prior knowledge or expectations concerning their efficiency, current input choice will be correlated with productivity. Coefficients on variable inputs will be biased upward as a result of this endogeneity or simultaneity problem, while the coefficient on capital will be biased downward provided the correlation between labor and capital is positive.

Third, in the presence of imperfect competition in input and/or output markets, the failure to take firm-level deviations from the industry-level price deflator into account will result in an omitted output and/or input price bias. The resulting bias(es) will, in a standard demand/supply framework, work in the opposite direction as the simultaneity bias, rendering any prior on the overall direction of the bias hard. Finally, if firms produce multiple products, which potentially differ in terms of their production technology and demand, an additional bias will be introduced in traditional TFP estimates. I now turn to the various estimators that have been introduced in the literature on consistent estimation of total factor productivity.

3 Total factor productivity estimation

3.1 Fixed effects estimation

By assuming that ω_{it} is plant-specific, but time-invariant; it is possible to estimate (2) using a fixed effects estimator (Pavcnik, 2002; Levinsohn and Petrin, 2003). The estimating equation then becomes:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_i + u_{it}^q \tag{6}$$

Equation (6) can be estimated in levels using a Least Square Dummy Variable Estimator (LSDV, i.e. including firm-specific effects) or in first (or mean) differences. Provided unobserved productivity ω_{it} does not vary over time, estimation of (6) will result in consistent coefficients on labor, capital and materials.

Origin of the bias	Definition	Direction of the bias	References
Selection bias	Endogeneity of attrition: Correlation between ε_{it} and K_{it} (the quasi-fixed input), conditional on being in the data set.	downward bias in β_k	Wedervang (1965) Olley and Pakes (1996) ABBP (2007)
Simultaneity bias	Endogeneity of inputs: Correlation between ε_{it} and inputs x_{it} if firms' prior beliefs about ε_{it} influence its choice of inputs.	upward bias in β_l upward bias in β_m downward bias in β_k	Marschak and Andrews (1944) Olley and Pakes (1996) Levinsohn and Petrin (2003) ABBP (2007) Ackerberg et al. (2006)
Omitted output price bias	Imperfect competition in output markets: Correlation between firm-level deviation of output price deflator $(p_{it} - \overline{p}_{it})$ and inputs x_{it}.	downward bias in β_l downward bias in β_m upward bias in β_k	Klette and Griliches (1996) Levinsohn and Melitz (2002) De Loecker (2007)
Omitted input price bias	Imperfect competition in input markets: Correlation between firm-level deviation of input price deflators $\left(p_{it}^{k,m} - \overline{p}_{it}^{k,m}\right)$ and inputs x_{it}.	downward bias in β_l downward bias in β_m upward bias in β_k	Levinsohn and Melitz (2002) Katayama et al. (2005) De Loecker (2007)
Multi-product firms	Endogenous product choice: Differences in production technologies across products produced by single firm.	undetermined	Bernard, Redding, Schott (2005) Bernard, Redding, Schott (2006b) De Loecker (2007)

Table 1: TFP estimation: Summary of methodological issues

Fixed effects or within estimators have a long tradition in the production function literature, in fact they were introduced to economics in this context (Mundlak, 1961; Hoch, 1962). By using only the within-firm variation in the sample, the fixed effects estimator overcomes the simultaneity bias discussed in the previous section (ABBP, 2007). Moreover, to the extent that exit decisions are determined by the time-invariant, firm-specific effects ω_i, and not by u_{it}^q, the within estimator also eliminates the selection bias, caused by endogenous exit in the sample. As a result, estimation of (6) using either the balanced or unbalanced (i.e. allowing for entry and exit) sample should result in similar estimates for the coefficients.

In spite of the attractive properties of the fixed effects estimator, it does not perform well in practice (ABBP, 2007). Estimation of (6) often leads to unreasonably low estimates of the capital coefficient. Moreover, Olley and Pakes (1996) perform fixed effects on the balanced and unbalanced sample and find large differences between the two sets of coefficients, suggesting the assumptions underlying the model are invalid. The time-invariant nature of ω_i in the fixed effects model has been relaxed by Blundell and Bond (1999) in the context of production functions, by allowing productivity to be decomposed into a fixed effect and an autoregressive AR(1)-component.

3.2 Instrumental variables (IV) and GMM

An alternative method to achieve consistency of coefficients in the production function is by instrumenting the independent variables that cause the endogeneity problems (i.e. the inputs in the production function) by regressors that are correlated with these inputs, but uncorrelated with unobserved productivity. To achieve consistency of this IV estimator, three requirements have to be met (ABBP, 2007). First, instruments need to be correlated with the endogenous regressors (inputs). Second, the instruments can not enter the production function directly and finally, instruments need to be uncorrelated with the error term.

Assuming input and output markets operate perfectly competitive, input and output prices are natural choices of instruments for the production function (ABBP, 2007). Other examples of instruments include variables that shift the demand for output or the supply of inputs. Like the fixed effects estimator, the IV estimator has not been particularly successful in practice. One of the obvious shortcomings of the technique is the lack of appropriate instruments in many data sets. Input and output prices are usually not reported in typical plant or firm level data sets and if they are reported, frequently not enough variation exists in the data in order to identify coefficients of the production function (ABBP, 2007). Moreover, while estimation using IV techniques overcomes the simultaneity bias (provided the instruments are appropriate), it does not provide a solution for the selection issues. If input prices are used as instruments for input quantities and if exit decisions are driven (in part) by changes in these input prices, results will remain biased.

In response to these unsatisfactory results, Blundell and Bond (1999) propose an extended GMM estimator. They attribute the bad performance of standard IV estimators to the weak instruments used for identification, i.e. lagged levels of variables are often used as instruments in the estimation in first differences. They propose an extended GMM estimator using lagged first-differences of the variables as instruments in the level equations and find that this estimator yields more reasonable parameter estimates. As already noted above, they also stress the importance of allowing for an autoregressive component in ω_{it}.

3.3 Olley-Pakes estimation algorithm

As an alternative to the methods discussed above; Olley and Pakes (1996) have developed a consistent semiparametric estimator. This estimator solves the simultaneity problem by using the firm's investment decision to proxy for unobserved productivity shocks. Selection issues are addressed by incorporating an exit rule into the model. In what follows, the proposed methodology will be discussed in somewhat more detail. It should be noted here however, that the focus in this section is on the estimation methodology. For the more technical aspects (and related proofs), the interested reader is referred to Ericson and Pakes (1995) and Olley and Pakes (1996).

Olley and Pakes (1996) were the first to introduce an estimation algorithm that takes both the selection and simultaneity problem explicitly into account. They develop a dynamic model of firm behavior that allows for idiosyncratic productivity shocks, as well as for entry and exit. At the start of each period, each incumbent firm decides whether to exit or to continue its operations. If it exits, it receives a particular sell-off value and it never re-enters. If it continues, it chooses an appropriate level of variable inputs and investment. The firm is assumed to maximize the expected discounted value of net cash flows and investment and exit decisions will depend on the firm's perceptions about the distribution of future market structure, given the information currently available. Both the lower bound to productivity (i.e. the cut-off value below which the firm chooses to exit) and the investment decision are determined as part of a Markov perfect Nash equilibrium and will hence depend on all parameters determining equilibrium behavior.

In order to achieve consistency, a number of assumptions need to be made. First, the model assumes there is only one unobserved state variable at the firm level, i.e. its productivity. Second, the model imposes monotonicity on the investment variable, in order to ensure invertibility of the investment demand function. This implies that investment has to be increasing in productivity, conditional on the values of all state variables. As a consequence, only non-negative values of investment can be used in the analysis. This condition needs to hold for at least some known subset of the sample (see below). Finally, if industry-wide price indices are used to deflate inputs and output in value terms to proxy for their respective quantities , it is implicitly assumed that all firms in the industry face common input and output prices (Ackerberg, Benkard, Berry and Pakes, 2007).

Starting out from the basic Cobb-Douglas production function[8] given by (2), the estimation procedure can be described as follows. Capital is a state variable, only affected by current and past levels of ω_{it}. Investment can be calculated as:

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

Hence, investment decisions at the firm level can be shown to depend on capital and productivity or $i_{it} = i_t (k_{it}, \omega_{it})$, where lower-case notation refers to logarithmic transformation of variables, as above. Provided investment is strictly increasing in productivity, conditional on capital, this investment decision can be inverted, allowing us to express unobserved productivity as a function of observables:

$$\omega_{it} = h_t (k_{it}, i_{it})$$

where $h_t (.) = i_t^{-1} (.)$. Using this information, (2) can be rewritten as:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + h_t (k_{it}, i_{it}) + u_{it}^q \tag{7}$$

[8]The production function in (2) differs from that employed by OP in two respects. First, OP include age as an additional state variable, which is omitted here. Second, OP start out from a value added production function, i.e. including only labor and capital as production factors.

Next, define the function $\varphi\left(i_{it}, k_{it}\right)$ as follows:

$$\varphi\left(i_{it}, k_{it}\right) = \beta_0 + \beta_k k_{it} + h_t\left(i_{it}, k_{it}\right)$$

Estimation of (7) proceeds in two steps (OP, 1996). In the first stage of the estimation algorithm, the following equation is estimated using OLS:

$$y_{it} = \beta_l l_{it} + \beta_m m_{it} + \varphi\left(i_{it}, k_{it}\right) + u_{it}^q \tag{8}$$

where $\varphi\left(i_{it}, k_{it}\right)$ is approximated by a higher order polynomial in i_{it} and k_{it} (including a constant term). Estimation of (8) results in a consistent estimate of the coefficients on labor and materials (the variable factors of production).

In order to recover the coefficient on the capital variable, it is necessary to exploit information on firm dynamics. Productivity is assumed to follow a first order Markov process, i.e. $\omega_{it+1} = E\left(\omega_{it+1} | \omega_{it}\right) + \xi_{it+1}$, where ξ_{it+1} represents the news component and is assumed to be uncorrelated with productivity and capital in period *t+1*. As noted above, firms will continue to operate provided their productivity level exceeds the lower bound, i.e. $\chi_{it+1} = 1$ if $\omega_{it+1} \geq \underline{\omega}_{it+1}$, where χ_{it+1} is a survival indicator variable. Since the news component ξ_{it+1} is correlated with the variable inputs; labor and material inputs are subtracted from the log of output. Considering the expectation of $E\left(y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1}\right)$, conditional on the survival of the firm results in the following expression:

$$\begin{aligned} &E\left[y_{it+1} - \beta_l l_{it+1} - \beta_m m_{it+1} | k_{it+1}, \chi_{it+1} = 1\right] \\ &\quad = \beta_0 + \beta_k k_{it+1} + E\left[\omega_{it+1} | \omega_{it}, \chi_{it+1} = 1\right] \end{aligned}$$

The second stage of the estimation algorithm can then be derived as follows:

$$\begin{aligned} y_{it+1} & \; -\beta_l l_{it+1} - \beta_m m_{it+1} \\ = & \; \beta_0 + \beta_k k_{it+1} + E\left(\omega_{it+1} | \omega_{it}, \chi_{it+1}\right) + \xi_{it+1} + u_{it+1}^q \\ = & \; \beta_0 + \beta_k k_{it+1} + g\left(P_{it}, \varphi_t - \beta_k k_{it}\right) + \xi_{it+1} + u_{it+1}^q \end{aligned} \tag{9}$$

where $E\left(\omega_{it+1} | \omega_{it}, \chi_{it+1}\right) = g\left(P_{it}, \varphi_{it} - \beta_k k_{it}\right)$ follows from the law of motion for the productivity shocks and P_{it} is the probability of survival of firm i in the next period[9], i.e. $P_{it} = \Pr\{\chi_{it+1} = 1\}$. A consistent estimate of the coefficient on capital is obtained by substituting the estimated coefficients on labor and materials from the first stage, as well as the estimated survival probability in (8). As in the first stage of the estimation procedure, the function $g(P_{it}, \varphi_{it} - \beta_k k_{it})$ is approximated using a higher order polynomial expansion in P_{it} and $\varphi_{it} - \beta_k k_{it}$. Finally, this results in the following estimating equation:

$$\begin{aligned} y_{it+1} & -\beta_l l_{it+1} - \beta_m m_{it+1} \\ = & \quad \beta_0 + \beta_k k_{it+1} + g\left(\widehat{P}_{it}, \widehat{\varphi}_t - \widehat{\beta}_k k_{it}\right) + \xi_{it+1} + u^q_{it+1} \end{aligned} \tag{10}$$

The coefficient on capital can then be obtained by applying Non-Linear Least Squares on (10).

3.4 Levinsohn-Petrin estimation algorithm

While Olley and Pakes (1996) use the investment decision to proxy for unobserved productivity; Levinsohn and Petrin (2003) rely on intermediate inputs as a proxy. The monotonicity condition of OP requires that investment is strictly increasing in productivity. Since this implies that only observations with positive investment can be used when estimating (8) and (10), this can result in a significant loss in efficiency, depending on the data at hand. Moreover, if firms report zero investment in a significant number of cases, this casts doubt on the validity of the monotonicity condition. Hence, Levinsohn and Petrin (2003) use intermediate inputs rather than investment as a proxy. Since firms typically report positive use of materials and energy in each year, it is possible to retain most observations; which also implies that the monotonicity condition is more likely to hold.

Their estimation algorithm differs from that introduced by OP in two important respects. First, they use intermediate inputs to proxy for unobserved productivity, rather than investment. This implies that intermediate inputs (materials in this case) are expressed as a function of capital and productivity, i.e. $m_{it} = m_t(k_{it}, \omega_{it})$. Provided the monotonicity condition is met and

[9] An estimate of P_{it} can be obtained by estimating a probit model, where the dependent variable is a survival dummy (i.e. dummy equal to one if the firm survives in a particular period). Left-hand side variables are the same polynomial terms used in the first stage of the estimation procedure, i.e. a higher-order polynomial in investment and capital, including a constant term. $\widehat{P}_{it}$ can then be obtained as the predicted survival probability from this regression.

materials inputs are strictly increasing in ω_{it}, this function can be inverted, again allowing us to express unobserved productivity as a function of observables, i.e. $\omega_{it} = s_t(k_{it}, m_{it})$, where $s_t(.) = m_t^{-1}(.)$. Using this expression, it is possible to rewrite (2), analogous to the OP-approach described above.

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + s_t(k_{it}, m_{it}) + u_{it}^q \tag{11}$$

It should be noted that the coefficient on the proxy variable, i.e. materials; is now only recovered in the second stage of the estimation algorithm, rather than in the first as for the OP approach. The second difference between the approach used by OP and LP is in the correction for the selection bias. While OP allow for both an unbalanced panel as well as the incorporation of the survival probability in the second stage of the estimation algorithm, LP do not incorporate the survival probability in the second stage; since the efficiency gains associated with it in the empirical results presented by OP were very small provided an unbalanced panel was used. Apart from using materials instead of investment as a proxy and omitting the survival correction in the second stage[10], estimation is fully analogous to the approach used by OP and summarized above. Moreover, Petrin, Levinsohn and Poi (2003) have developed a Stata program implementing the LP approach (*levpet*). For further details on the LP approach, I refer to LP and Petrin et al. (2003).

3.5 Olley-Pakes versus Levinsohn-Petrin

As was noted above, the OP and LP estimation algorithms are analogous apart from the use of different proxies and the in- or exclusion of the survival probability to correct for the selection bias. How then, is one to choose among the two estimators? I will briefly discuss some of the results emerging from the literature here.

It is useful to start with the most obvious shortcoming of the OP estimation algorithm, i.e. the invertibility condition, which implies that only firms with positive investment can be included in the analysis. Although consistent production function coefficients can be obtained by estimating (10) for the subset in the sample with recorded positive investment; this implies a loss in efficiency and, particularly if there are few firms with positive investment flows in the industry, can cast doubt on the monotonicity condition (see above).

[10] In principle it is possible to implement the explicit correction for firm survival in the LP estimation algorithm.

Moreover, according to Ackerberg, Caves and Frazer (2006), collinearity between labor and the non-parametric terms (i.e. the polynomial in materials and capital for LP and in investment and capital for OP) in the first stage of the estimation algorithm can cause the labor coefficient to be unidentified. This collinearity arises from the fact that labor, like materials and capital, needs to be allocated in some way by the firm, at some point in time. While this problem can arise in the context of the OP and LP estimator, it is particularly problematic for the LP estimator.

For the LP estimator, since labor and materials are both chosen simultaneously, a natural assumption could be that they are allocated in similar ways. However, this would imply that labor and materials are both chosen as a function of productivity and capital:

$$m_{it} = f_t\left(\omega_{it}, k_{it}\right)$$

$$l_{it} = g_t\left(\omega_{it}, k_{it}\right)$$

Hence, both labor and materials depend on the same state variables. 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 (Ackerberg et al., 2006):

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

Since it is not possible to simultaneously estimate a non-parametric function of ω_{it} and k_{it} together with the coefficient on the labor variable, which is also a function of those same variables; the labor coefficient will not be identified in the first stage. Hence collinearity between the labor variable and the non-parametric function in the first stage can cause the labor coefficient to be unidentified. Ackerberg, Caves and Frazer further investigate to what extent plausible assumptions can be made about the data generating process for labor in order to "save" the LP first stage estimation, with little success.

As noted above, this collinearity problem can also arise in the context of the OP estimation procedure. However, for the OP estimator, identification of the labor coefficient can be achieved by assuming that labor is not a perfectly variable input and that firms decide on the allocation of labor without perfect information about their future productivity (i.e. investment and labor are determined by different information sets). If this assumption holds for the data at hand, the labor 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 labor prior to choosing material inputs will make the choice of the latter directly dependent on the choice of labor inputs, again preventing identification of the labor 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 labor will not directly affect its investment decisions (Ackerberg et al., 2006).

Ackerberg, Caves and Frazer suggest an alternative estimation procedure, where the coefficient on labor (in a value added production function) 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.

Moreover, in the presence of imperfect competition in input or output markets, consistency of either the OP or LP estimator is likely to break down, as an omitted price variable will bias results. Therefore, the OP algorithm has been augmented to take imperfect competition in output markets explicitly into account (De Loecker, 2007, see below). For LP however, De Loecker (2007, Appendix C) shows that imperfect competition in output markets is likely to invalidate the invertibility condition, while it has no effect on the monotonicity condition of OP. Therefore, even if the LP estimation algorithm is augmented with the correction for imperfect competition (discussed below), coefficients are likely to be biased. Hence, I will focus on the OP algorithm in what follows.

3.6 Extensions of the Olley-Pakes methodology

Many of the extensions and alternatives that emerge from the literature are still work in progress, making it particularly hard to choose among the many candidates. For a recent technical review of a number of extensions to the OP methodology, I refer to ABBP[11] (2007). Alternatives to the semiparametric estimators of OP and LP are proposed by (among others) Katayama et al. (2005). However, a full discussion of these works lies beyond the scope of the present paper.

[11] ABBP focus on the assumptions underlying the semiparametric estimators introduced by OP and LP and show how to test their validity and how to relax some of them; they do not treat the bias introduced by endogenous product choice or by imperfect competition in input and output markets explicitly.

As was noted in section 2, De Loecker (2007) implements the correction for the omitted output price bias, introduced by Klette and Griliches (1996) in the OP estimation algorithm. In what follows, the specifics of his model will be discussed. While De Loecker (2007) also introduces a correction for multi-product firms, I have elected not to discuss this extension here for two reasons. First, in the absence of product-level data on inputs and outputs, consistent estimation of TFP can only be obtained by either focusing on single-product firms or by allowing the parameters of the production technology to vary across firms making different products (BRS, 2005). Although De Loecker (2007) is able to exploit information on which products a firm produces, allowing him to introduce product level demand rather than industry level demand as well as to control for the number of products a firm produces; the production technology is still (necessarily) assumed to be identical across products in an industry.

Moreover, BRS (2006b) find that more than 60 percent of US firms alter their product mix every five years. This implies that any information on the product space firms are active in, would have to be dynamic in nature[12]. Since typical annual accounts data usually provide no or very limited information at the relevant product level and given the remaining biases in the resulting production function coefficients in the absence of (dynamic) product-level data on inputs and outputs, I will restrict attention to single-product firms.

The relevant model to start from in the presence of imperfect competition in the output market is given by (4). In order to estimate (4) consistently without information on establishment-level prices, it is necessary to impose some structure on the demand system, which will be used to implicitly solve for the firm-level prices. Following De Loecker (2007), I start out from a simple conditional (Dixit-Stiglitz) demand system[13]:

$$Q_{it} = Q_{Jt} \left(\frac{P_{it}}{P_{Jt}} \right)^{\eta} \exp\left(u_{it}^{d} \right)$$

where Q_{it} represents demand for the firm's product, Q_{Jt} is industry output at time t, $\frac{P_{it}}{P_{Jt}}$ is the price of firm i relative to the average price in industry

[12] Although De Loecker has very detailed information on which firms are active in which sectors, the data are only available for 2001. Hence the firm-level product mix is necessarily assumed to be constant over the sample period in his analysis.

[13] The industry is assumed to be characterized by product differentiation. A key characteristic of Dixit-Stiglitz demand is that the price (substitution) elasticities are constant over time and independent of the number of varieties.

J, u^d_{it} is an idiosyncratic firm-specific demand shock and η is the elasticity of substitution (demand) between differentiated goods in the industry ($-\infty < \eta < -1$).

Taking natural logarithms results in the following expression for the demand system.

$$q_{it} = q_{Jt} + \eta p_{it} - \eta p_{Jt} + u^d_{it} \tag{12}$$

It is possible to derive an expression for p_{it} from (12) and substitute the result into (4).

$$p_{it} = \frac{1}{\eta}\left(q_{it} - q_{Jt} - u^d_{it}\right) + p_{Jt}$$

$$\widetilde{r}_{it} = p_{it} + y_{it} - \overline{p}_{it} = \frac{1}{\eta}\left(q_{it} - q_{Jt} - u^d_{it}\right) + p_{Jt} + y_{it} - \overline{p}_{it}$$

Using the fact that changes in the industry-wide price index $\overline{p}_{it}$ can be considered as a weighted average of the changes in firm-specific prices, i.e. $\overline{p}_{it} = p_{Jt}$, results in the following relationship:

$$\widetilde{r}_{it} = \frac{\eta+1}{\eta}\left(\beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + u^q_{it}\right) - \frac{1}{\eta} q_{Jt} - \frac{1}{\eta} u^d_{it} \tag{13}$$

where ω_{it} will be proxied by the investment decision as in section 3.3. Hence, it is clear from (13) that consistent estimation in the presence of imperfectly competitive output markets requires adding a term to the production function. By putting structure on the demand system, it is possible to proxy for unobserved firm-level prices by adding industry output as an additional regressor in the production function[14]. Specifically, the final estimating equation looks as follows:

$$\widetilde{r}_{it} = \alpha_0 + \alpha_k k_{it} + \alpha_l l_{it} + \alpha_m m_{it} + \omega^{'}_{it} + u^{'q}_{it} + \alpha_\eta q_{Jt} - u^{'d}_{it} \tag{14}$$

where $\alpha_h = \left(\left(\eta+1\right)/\eta\right)\beta_h$ for $h = 0, l, m, k$; $\omega^{'}_{it} = \left(\left(\eta+1\right)/\eta\right)\omega_{it}$ and $\alpha_\eta = (-1/\eta)$. The final production function coefficients can be obtained by multiplying the coefficients obtained in (14) with the relevant mark-up, i.e. $\eta/\left(\eta+1\right)$. Similarly, firm-level productivity is now obtained as follows:

[14] Ornaghi (2006) invalidates the correction suggested by Klette and Griliches by confirming the existence of asymmetric biases among the input coefficients introduced by the use of deflated values of inputs and outputs rather than observed quantities. Given this asymmetric bias, multiplying all input coefficients with an identical upward correction term (i.e. the mark-up) as illustrated in (15) can not yield unbiased input coefficients.

$$\hat{\omega}_{it} = \left(\frac{\hat{\eta}}{\hat{\eta}+1}\right)\hat{\omega}_{it}^{'} = \left(\frac{\hat{\eta}}{\hat{\eta}+1}\right)(\tilde{r}_{it} - \hat{\alpha}_k k_{it} - \hat{\alpha}_l l_{it} - \hat{\alpha}_m m_{it} - \hat{\alpha}_\eta q_{Jt}) \quad (15)$$

Hence, for the OP estimator including the correction for market power, productivity as obtained in (3) additionally needs to be multiplied by the relevant mark-up; as shown in (15). Although this correction simply implies a rescaling of firm-level productivity in this particular case, it is straightforward to interact industry output at a more disaggregated level with sector dummies at an equal level of aggregation to allow the demand elasticity and relevant mark-up to vary across sub-sectors[15]. Allowing the demand elasticity to vary across sub-sectors in (14) leads to the following estimating equation (De Loecker, 2007):

$$\widetilde{r}_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \omega_{it}^{'} + u_{it}^{'q} + \sum_{s=1}^{M} \alpha_{\eta s} q_{Jts} I_{is} - u_{it}^{'d} \quad (16)$$

where s represents the sub-sector and M equals the total number of sub-sectors. I_{is} is a dummy variable equal to 1 if a firm is active in a given sub-sector and q_{Jts} is the relevant industry demand shifter, proxied by output in the different sub-sectors. The number of estimated elasticities η_s equals the number of sub-sectors in the industry. Industry output is simply replaced in the estimation by $\sum_{i=1}^{M} \alpha_{\eta s} q_{Jts} I_{is}$. It should be noted that if demand parameters are allowed to vary across sub-sectors; the resulting production coefficients β_h will also be specific to those sub-sectors, since the estimates obtained from estimating (16) have to be transformed using the relevant (sub-sector) mark-up.

3.7 Summary of estimation algorithms

Table 2 summarizes the different estimation algorithms discussed in this section. While fixed effects and instrumental variables methods are theoretically able to solve the simultaneity bias introduced when estimating (2) using OLS; their application has not been entirely successful. Likely causes for the failure of both techniques to produce sensible and unbiased results are the lack of time-invariance of ω_{it} in the case of fixed effects and the lack

[15] De Loecker additionally includes product dummies in the first stage of the estimation algorithm to control for unobserved product quality differences.

of good instruments in the case of IV estimation. Blundell and Bond (1999) have developed an extended GMM estimator, taking some of these issues into account.

Both semiparametric estimators (OP and LP) are able to resolve simultaneity issues by using a proxy variable to substitute for unobserved productivity; assuming a strict monotonicity condition holds and ω_{it} is the only unobserved firm-level variable (i.e. the scalar unobservable). While it is possible to take selection issues into account by using an unbalanced panel for both estimators, only the OP estimation algorithm explicitly takes the survival probability at the firm level into account in the second stage of the estimation algorithm. Extensions have been developed, mainly in the context of the OP procedure, to take imperfect competition in output markets, as well as multi-product firms into account (De Loecker, 2007).

4 Empirical application: Food and beverages industry in Belgium

In what follows, I will illustrate the different methodologies introduced in the previous section, using firm-level data on the Belgian food and beverages industry. The data set is constructed on the basis of the Belfirst database, which groups annual accounts data on the entire population of limited-liability firms located in Belgium. The database is commercialized by BvDEP (2006). Firms are uniquely defined by their VAT number and data on employment, net value added, total fixed assets etc. are available for the years 1996-2005. Firms are classified into sectors according to the NACE-Bel nomenclature, i.e. a five-digit extension of the NACE (Revision 1) classification commonly used for European statistics[16]. Producer price indices used to deflate firm-level output are available from Eurostat (2007) at the three-digit Nace level. Deflators for material inputs and investment were obtained from Belgostat (2007).

Following Mata and Portugal (1994); Mata et al. (1995) and Van Beveren (2007b); entry and exit in the sample are defined as economic exit and entry[17], implying that exit occurs if a firm's employment drops to zero in a

[16] The NACE Rev. 1 classification can be downloaded from the Eurostat Ramon server: http://europa.eu.int/comm/eurostat/ramon/.

[17] Although the Belfirst database reports firms' legal status and hence also legal exit; I do not rely on this measure for two reasons. First, inspection of the data reveals that

Estimation algorithm	Assumptions	Resolved issues	References
Fixed effects	ω_{it} is plant-specific, but time-invariant.	Simultaneity Selection if $\omega_{it} = \omega_i, \forall i$	Mundlak (1961) Hoch (1962) ABBP (2007)
Instrumental variables & GMM	Correlation between instruments and endogenous regressors. No correlation between instruments and error term.	Simultaneity Selection (unbalanced panel)	Blundell and Bond (1999) ABBP (2007)
Semiparametric estimator: Olley & Pakes	Invertibility condition: investment has to be strictly increasing in ω_{it}. Scalar unobservable assumption: ω_{it} is only unobserved state variable.	Simultaneity Selection (unbalanced panel) Selection (survival probability)	Olley and Pakes (1996) ABBP (2007) Ackerberg et al. (2006)
Semiparametric estimator: Levinsohn & Petrin	Invertibility condition: m_{it} has to be strictly increasing in ω_{it}. Scalar unobservable assumption: ω_{it} is only unobserved state variable.	Simultaneity Selection (unbalanced panel)	Levinsohn and Petrin (2003) Petrin et al. (2003) Ackerberg et al. (2006)
OP with imperfect competition in output markets	Assumptions OP.	Simultaneity Selection (unbalanced panel) Selection (survival probability) Omitted output price bias	Klette and Griliches (1996) Levinsohn and Melitz (2002) De Loecker (2007)
Extended OP including correction for multi-product firms	Assumptions OP. Common production technology for all products of a firm. Demand elasticity is common across products and constant.	Simultaneity Selection (unbalanced panel) Selection (survival probability) Omitted output price bias Endogenous product choice	Klette and Griliches (1996) Levinsohn and Melitz (2002) De Loecker (2007)

Table 2: TFP estimation: Summary of estimation algorithms

particular year and entry takes place if there was no previous employment recorded. Firms exhibiting irregular exit or entry patterns are omitted from the sample. Similarly, in order to verify that no re-entry occurs after a firm exits, the last two years in the sample are dropped.

There are several reasons why the evolution of TFP in the food and beverages sector in Belgium is of interest. First, the sector represents a significant share of industrial employment in Belgium, accounting for 14.2 percent of the total (CRB, 2004), second only to the metals industry (16 percent). Moreover, the outbreak of the dioxin crisis in 1999, when excessive concentrations of dioxin were found in eggs, chickens, milk and pork; resulting from contaminated animal food (The Economist, 1999); led to a period of significant restructuring and increasing investments in the sector; reflected in the sample by high entry and exit rates (see below). Given these preliminaries, it can be expected that some of these events will be reflected in the industry's TFP performance.

Using the Belfirst database, I was able to collect information on all firms active in the food and beverages sector (NACE 15). Firms with no recorded data on one of the variables used in the empirical analysis are omitted[18], as well as firms producing multiple products. To identify multi-product firms, I rely on the number of five-digit NACE-Bel codes a firm lists, i.e. the most detailed level available in the database. If a firm is active in more than one five-digit sector, it is omitted from the analysis. Finally, the data are checked for outliers and gaps. Firms exhibiting variable input growth of more than 200 percent (employment and materials inputs) in one year or output growth of more than 500 percent are excluded from the sample.

This results in a final sample of 1,025 firms (5,551 observations). Table 3 reports summary statistics for the sample for the period 1996-2003. From the table it is clear that the average firm in the sample is relatively large (average employment amounts to 54.61 employees). By comparison, in the full sample of firms active in sector 15, the average firm employs about 30 people. As

the official date associated with the legal status in the database often does not concur with the actual time the firm exits the market. Second, communications with Bureau Van Dijk made clear that although the legal status is correctly reported whenever available, many companies fail to report their annual accounts after ending their activities. For the specifics associated with the exit and entry variables, I refer to Van Beveren (2007a).

[18] Belgian accounting rules only require firms to report full annual accounts (including data on turnover) once a certain threshold in terms of employment, total assets or turnover is reached. Therefore, the sample necessarily excludes smaller firms.

noted above, the period considered here involved significant restructuring in the sector, translated in high entry and exit rates. Specifically, 184 firms (18 percent) enter the sample between 1996 and 2003; while 131 firms (13 percent) exit over the same period.

Table 4 reports the production function coefficients obtained using the different methodologies introduced in section 3. All reported estimates are obtained for the unbalanced panel of firms (allowing for implicit entry and exit); apart from the fixed effects estimator, where I report both the unbalanced and balanced sample result. The first column in the table reports the number of observations associated with each specific estimator and clearly shows one of the main advantages of the LP estimator compared to OP. Since material inputs are used to proxy for unobservable productivity; I am able to retain the full sample of firms in the first estimation stage; while for OP, only those observations with positive investment can be retained in the first stage. In the second stage, one year of observations is lost due to the dynamic nature of the model, both for OP and LP.

All estimations reported in table 4 are performed in Stata 10. For the OLS and fixed effects estimators, built-in commands *reg* and *xtreg* are used. The GMM estimator is obtained using the *xtabond2* command, due to Roodman (2006). No built-in or user-developed command exists to date to implement the OP estimator[19]; but Arnold (2005) provides some practical tips, particularly on the implementation of the nonlinear second stage. The LP estimator was implemented using the *levpet* command, due to Petrin et al. (2003).

In order to interpret the estimated coefficients, it is useful to briefly go back to table 1. In the third column of this table, the general direction of the biases introduced by the different endogeneity issues are given. Theoretically, the fixed effects estimator corrects for both the simultaneity and selection bias, hence the coefficients on the variable inputs (labor and materials) are expected to be lower compared to the OLS result; while the coefficient on capital is expected to be higher. While the coefficients on the variable inputs in table 4 are in line with expectations (β_l and β_m are lower compared to the first row); the capital coefficient is still very low, both for the balanced and unbalanced sample.

[19] A user-developed command, *opreg*, has recently been made available in Stata, due to Yasar, Raciborski and Poi (2008). I have not relied on this command for the empirical estimations.

Variable	N	Mean	Standard Deviation	Minimum	Maximum
Real output ($\widetilde{R}_{jt}$, €x 1,000)	5,551	19,454.79	61,007.18	0.97	950,812.10
Employment (L_jt)	5,551	54.61	181.91	1	3,443.00
Real materials ($\widetilde{M}_{jt}$, €x 1,000)	5,551	16,600.85	49,454.16	1.14	807,434.90
Real capital ($\widetilde{K}_{jt}$, €x 1,000)	5,551	3,036.16	15,605.24	0.99	447,185.80
Real (pos.) investment ($\widetilde{I}_{jt}$, €x 1,000)	3,588	662.46	2,653.91	0.01	61,377.32

Real values are obtained by deflating monetary values using three-digit producer price indices obtained from Eurostat. Output is defined as turnover of the firm. Employment is measured as the number of employees (full-time equivalents). The materials variable includes raw materials, consumables, services and other goods. Capital is defined as total fixed tangible assets. Investment is calculated on the basis of firm-level capital, using a standard depreciation rate of 15 percent. Data pertain to the Food and Beverages sector (NACE 15) in Belgium, for the years 1996 to 2003.

Table 3: Summary statistics of key variables

Method	N	Labor β_l	Labor SE	Materials β_m	Materials SE	Capital β_k	Capital SE
OLS	5,551	0.2113***	[0.0152]	0.7700***	[0.0138]	0.0266***	[0.0072]
Fixed Effects (balanced)	3,568	0.1696***	[0.0192]	0.6474***	[0.0419]	0.0277***	[0.0063]
Fixed Effects (unbalanced)	5,551	0.1685***	[0.0166]	0.6814***	[0.0379]	0.0248***	[0.0052]
GMM	5,551	0.1520***	[0.0368]	0.7890***	[0.0434]	0.0372**	[0.0173]
OP (no survival correction)	3,588	0.1925***	[0.0153]	0.7722***	[0.0150]	0.0445**	[0.0195]
OP (survival correction)	3,588	0.1925***	[0.0153]	0.7722***	[0.0150]	0.0453***	[0.0167]
Levinsohn-Petrin	5,551	0.2139***	[0.0148]	0.7915***	[0.0802]	0.0484**	[0.0205]
De Loecker (1)	3,588	$\alpha_l = 0.1947$***	[0.0153]	$\alpha_m = 0.7686$***	[0.0151]	$\alpha_k = 0.0461$*	[0.0240]
Transformed coefficients DL	$\alpha_q = 0.2926$***	0.2707***	[0.0223]	1.0837***	[0.0426]	0.0654**	[0.0338]
	[0.0199]						

Values are coefficients, standard errors reported between brackets. (1) The coefficients for the DL estimator are obtained by multiplying the alpha's with the relevant mark-up. The elasticity of substitution η equals $(-1/\alpha_q)$ or -3.42. The relevant mark-up therefore equals $\eta/(\eta+1) = 1.41$.

Table 4: Production function estimates

Moreover, as was discussed in section 3, comparing the results of the balanced and unbalanced sample for the FE estimator enables us to determine whether the FE estimator adequately corrects for the selection bias; i.e. whether exit decisions at the firm level are only determined by the time-invariant, firm-specific effects ω_i. Given the small differences between the coefficients obtained for the balanced and unbalanced sample; results in table 4 suggest that the FE estimator is able to correct for the selection bias in the sample.

Since the GMM estimator is theoretically able to correct for the simultaneity bias, β_l and β_m in row 4 of table 4 are expected to be lower, while β_k should increase compared to their OLS counterparts; similarly to the FE estimator. Results in row 4 show a lower labor coefficient and higher capital coefficient (in line with expectations); but lower coefficient on materials (not in line with expectations).

The last four rows in table 4 display the production function coefficients for the semiparametric estimators of OP (both with and without explicit correction for firms' survival probability), LP and De Loecker. Comparing OP estimates to the OLS estimates in the first row, shows that the coefficients on both labor and materials are lower compared to OLS results, while the capital coefficient is significantly higher; which is in line with expectations. Including the estimated survival probability in the second stage of the estimation algorithm has virtually no impact on the capital coefficient. This result is in line with the findings of OP, who similarly found no significant improvement in the capital coefficient from the explicit correction for survival when an unbalanced panel is used. Although the LP coefficient on capital is higher than its OLS counterpart, the labor and materials coefficients are somewhat higher than the OLS estimates.

The final row of table 4 summarizes the results of estimating (14) using the estimation algorithm introduced[20] by De Loecker (2007). Essentially, this amounts to the inclusion of industry output in the first stage of estimation and subtracting the resulting coefficient times output from the left-hand-side in (10). Industry output is calculated at the three-digit level in each year

[20] Although the correction for market power in output markets was originally suggested by Klette and Griliches (1996), De Loecker was the first to implement this correction into the semiparametric estimation framework introduced by Olley and Pakes (1996). Abraham, Konings and Slootmaekers (2007a) report results of the DL estimator as a robustness check in their paper on FDI spillovers in China.

as the share-weighted average of firm-level outputs, where shares are based on deflated revenues. This comes from the observation that the industry price index (which is available at the three-digit level) represents a share-weighted average of firm-level prices, where weights are output shares (De Loecker, 2007). For now, the elasticity of demand (substitution) is assumed to be identical across the different subsectors within the food and beverages industry.

As was shown in section 3, the coefficient on industry output α_q relates to the elasticity of demand in the following way: $\alpha_q = (-1/\eta)$. Moreover, using the demand elasticity, which amounts to -3.42; it is possible to calculate the relevant mark-up at the industry level $\eta/(\eta + 1)$, equal to 1.41. This estimate is somewhat higher than the result found by Konings (2001), who find a mark-up of 1.30 for the food and beverages industry in Belgium in the period 1992-1996. The last row in table 4 further reports both the estimated coefficients and the true production coefficients $\beta_h = (\eta/\eta + 1)\,\alpha_h$. Consistent with the theoretically predicted biases in table 1, the coefficients on labor and materials are significantly higher compared to the OP coefficients without including industry output. However, the coefficient on capital is somewhat higher compared to the basic OP results, which is not in line with expectations.

As was indicated in section 3, it is straightforward to allow the demand elasticity to vary over the different three-digit industries by interacting industry output with the respective industry dummies in (16). Since this results both in different demand elasticities and associated mark-ups; production function coefficients also become specific for each separate three-digit industry in this case. However, note that while production coefficients become variety-specific in this case, the production technology is still assumed to be constant for all three-digit industries within the food and beverages sector.

Table 5 reports the results of estimating (16) for the sample of single-product firms in the food and beverages industry. The first row in table 5 shows the estimated coefficients α_h. Compared to the estimated coefficient for the constant-elasticity estimator reported in the last row of table 4, the labor and materials coefficients are very similar, while the capital coefficient is somewhat higher. Turning to the industry-specific output coefficients, it is clear that large variation exists between the different three-digit subsectors of the food and beverages industry. Calculated demand elasticities vary between -2.8 and -3.6; associated mark-ups range between 1.39 and 1.56.

Three-digit industry NACE	Description	Output Coefficient	Demand Elasticity	Mark-up	Labor Coefficient	Materials Coefficient	Capital Coefficient
-	$\alpha_h (h = l, m, k)$	-	-	-	0.1948***	0.7685***	0.0569***
					[0.0153]	[0.0151]	[0.0215]
151	Meat (products)	0.3348***	-2.9869	1.5033	0.2896***	1.1592***	0.0863***
		[0.0224]			[0.0251]	[0.0517]	[0.0335]
152	Fish(products)	0.3552***	-2.8154	1.5508	0.2981***	1.1931***	0.0888***
		[0.0239]			[0.0265]	[0.0577]	[0.0347]
153	Fruit and vegetables	0.3145***	-3.1799	1.4587	0.2802***	1.1215***	0.0835***
		[0.0218]			[0.0237]	[0.0477]	[0.0323]
154	Oils and fats	0.3587***	-2.7881	1.5593	0.2999***	1.2003***	0.0894***
		[0.0243]			[0.0270]	[0.0588]	[0.0347]
155	Dairy products	0.2951***	-3.3888	1.4186	0.2728***	1.0919***	0.0813***
		[0.0197]			[0.0227]	[0.0416]	[0.0314]
156	Grain mill products	0.3026***	-3.3046	1.4339	0.2780***	1.1126***	0.0828***
		[0.0224]			[0.0235]	[0.0446]	[0.0320]
157	Prepared animal feeds	0.3103***	-3.2226	1.4499	0.2786***	1.1151***	0.0830***
		[0.0206]			[0.0238]	[0.0438]	[0.0321]
158	Other food products	0.2871***	-3.4831	1.4027	0.2692***	1.0774***	0.0802***
		[0.0194]			[0.0220]	[0.0407]	[0.0309]
159	Beverages	0.2784***	-3.592	1.3858	0.2656***	1.0631***	0.0791***
		[0.0184]			[0.0216]	[0.0377]	[0.0304]

Values are coefficients, standard errors reported between brackets. The variety-specific production function coefficients are obtained by multiplying the alpha's (given in the first row) with the relevant mark-up. The elasticity of substitution (demand) η is obtained as the inverse and negative of the output coefficient. The relevant mark-up equals $\eta/(\eta+1)$.

Table 5: Production function estimates: Variety-specific demand

These differences point to the importance of allowing the demand (substitution) elasticity to vary across different sub-sectors of a particular industry. As a consequence, variety-specific production coefficients also vary considerably across the different three-digit industries.

Two caveats should be noted here. First, I have continued to assume throughout that input prices for materials (capital) at the firm level are adequately captured by the materials (investment) deflator. To the extent that input price differences are translated into output price deviations, which are taken into account using industry output, this should partly take care of the omitted input price bias (De Loecker, 2007). However, as was already noted in section 2, a formal solution to this bias (in the absence of firm-level data on input prices) has yet to be introduced.

Second, the selection of single-product firms in the sample is obtained by resorting to the NACE-Bel codes reported by firms in their annual accounts, where the codes typically relate to the latest year available. Hence, the selection of firms is made in a particular year, whereas it is quite possible that some of these firms produced multiple products in any of the previous years.

The production function coefficients obtained in tables 4 and 5 can be used to calculate firm-level productivity for each of the sample years. By imposing coefficient stability on the model, it is possible to retain the full sample of firms for all estimators, even in the absence of positive investment (as for the OP estimators). Firm-level productivity for the OLS, fixed effects, GMM, OP (with and without survival correction) and LP estimators is obtained on the basis of (3). For the OP estimator including the correction for market power (De Loecker, with or without variety-specific demand), productivity as obtained in (3) additionally needs to be multiplied by the relevant mark-up; as was shown in (15).

Finally, using the estimates of firm-level productivity obtained from applying (3) and (15) to the sample using the production function coefficients from tables 4 and 5, it is possible to calculate aggregate industry productivity for each year in the sample as a weighted average of firm-level TFP:

$$\hat{P}_{Jt} = \sum_{i=1}^{N_t} s_{it} \hat{\Omega}_{it} \tag{17}$$

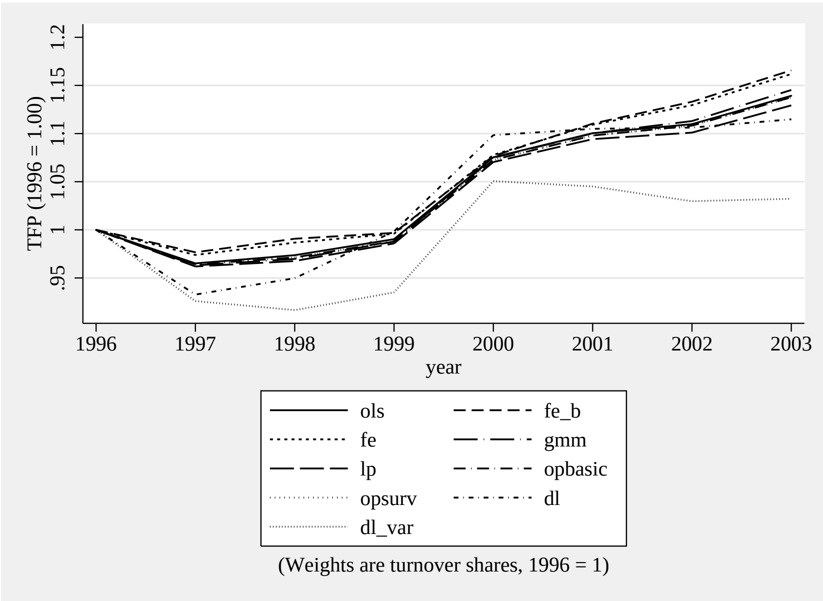

Figure 1: Weighted productivity index: Comparison estimation methods

where s_{it} is a firm-specific weight, equal to $(S_{it}/(\sum_i S_{it}))$ and S represents either turnover or employment (De Loecker and Konings, 2006). Normalizing this index to 1 in 1996 allows us to compare the evolution of aggregate TFP in the food and beverages industry for the different estimators discussed here.

Figure 1 shows the evolution of industry productivity between 1996 and 2003, using turnover shares as weights. From the figure, it is clear that TFP in the food and beverages industry exhibits a clear upward trend in the period following the dioxin crisis of 1999. However, whereas TFP continues to increase until 2002 when imperfect competition in output markets is not taken into account; TFP estimated using the DL methodology increases sharply between 1999 and 2000 and exhibits a more of less stable pattern after that. For the DL estimator with variety-specific demand, this pattern is even more apparent. Moreover, compared to the other estimators shown in figure 1, TFP calculated using the coefficients of table 5 declines more sharply prior to 1999 and grows less strongly after 1999. These results suggest that imperfect competition in output markets, when not taken into account in the production function estimation, may yield misleading results concerning the timing and magnitude of productivity shocks. The different growth pattern observed for the DL estimator with and without variety-specific demand further suggests that it is important to take the demand structure into account at the appropriate level of aggregation[21].

To assess whether the evolution of aggregate TFP in the food and beverages industry is due to firm-level improvements in TFP or rather to the reallocation of market shares between firms, various decompositions can be used (De Loecker and Konings, 2006). I will rely on the decomposition[22] introduced by Olley and Pakes (1996), who decompose aggregate productivity into a *within* component and a *covariance* term in the following way:

$$\hat{P}_{Jt} = \sum_{i=1}^{N_t} s_{it}\hat{\Omega}_{it}$$

$$\hat{P}_{Jt} = \sum_{i=1}^{N_t} (\bar{s}_t + \Delta s_{it}) \left(\bar{\hat{\Omega}}_t + \Delta\hat{\Omega}_{it}\right)$$

$$\hat{P}_{Jt} = \left(N_t \bar{s}_t \bar{\hat{\Omega}}_t\right) + \sum_{i=1}^{N_t} \left(\Delta s_{it}\Delta\hat{\Omega}_{it}\right)$$

$$\hat{P}_{Jt} = \bar{\hat{P}}_{it} + \sum_{i=1}^{N_t} \left(\Delta s_{it}\Delta\hat{\Omega}_{it}\right)$$

where $\bar{\hat{P}}_{it}$ is the unweighted average of plant-level total factor productivity and $\sum_{i=1}^{N_t} \left(\Delta s_{it}\Delta\hat{\Omega}_{it}\right)$ refers to the sample covariance between TFP and output (or employment) shares. The results of applying this decomposition using either turnover (left-hand side) or employment shares (right-hand side) for the TFP measure of De Loecker allowing for three-digit industry-specific demand elasticities, are displayed in table 6. The first column for each type of share consists of the share-weighted average productivity measured calculated on the basis of (17), normalized to 1 for 1996. The second and third column show the percentage contribution of the within productivity component and the reallocation share to aggregate weighted TFP respectively.

[21] Ideally, this would be at the product level. However, this would require not only information on aggregate product output, but also on product-level price evolutions (indices). One might also argue that in such a case, it is preferable to allow not only the industry output coefficient, but also the input coefficients to vary across products, i.e. to estimate a separate production function for each of the products (or sub-sectors in the absence of product-level information).

[22] An alternative to the OP decomposition is provided by Foster et al. (2006) . In addition to a within firm and reallocation term, they allow for a separate net-entry and interaction term. Given the complexity of their decomposition, it is beyond the scope of the present paper to apply it here.

Year	Turnover shares			Employment shares		
	Weighted Index (1996 = 1)	Mean TFP (%)	Reallo-cation (%)	Weighted Index (1996 = 1)	Mean TFP (%)	Reallo-cation (%)
1996	1.000	102.71	-2.71	1.000	107.18	-7.18
1997	0.9260	101.95	-1.95	0.9420	104.58	-4.58
1998	0.9166	101.09	-1.09	0.9338	103.54	-3.54
1999	0.935	100.96	-0.96	0.9637	102.22	-2.22
2000	1.0506	101.14	-1.14	1.0791	102.76	-2.76
2001	1.0451	100.84	-0.84	1.0748	102.32	-2.32
2002	1.0297	100.51	-0.51	1.0687	101.06	-1.06
2003	1.0323	99.95	0.05	1.0855	99.19	0.81

Weighted average productivity is calculated according to (17), weights are firm-level turnover or employment shares.

Table 6: Decomposition aggregate TFP: De Loecker methodology

From table 6, it is clear that most of the productivity improvements realized in the food and beverages sector since 1996 have been associated with within firm productivity growth. When employment shares rather than turnover shares are used (right-hand side of the table), the reallocation share is somewhat larger than for the case of turnover shares. Hence, I conclude that most of the productivity increases realized in the food and beverages industry in Belgium following the dioxin scandal in 1999 were due to the average firm becoming more productive, while reallocation of market share (either in terms of employment or turnover) has only played a minor role. Reallocation shares are consistently negative throughout the sample period, both using turnover and employment shares, with the exception of 2003, when it becomes positive in both cases.

For comparison purposes, table 7 summarizes the results of the OP decomposition for each of the different estimators listed in table 2. The table shows, apart from weighted normalized TFP in 2003 for each of the estimators, the average shares of unweighted average TFP and the sample covariance term in aggregate weighted industry productivity. Values reported are eight-year averages. Although the within firm growth component dominates regardless of the estimators applied to calculate industry productivity, there are some important differences worth noting.

Of the eight decompositions summarized in table 7, five yield similar results. Specifically, for the OLS, GMM, OP and De Loecker estimators the sample covariance terms (both for turnover and employment) are small and positive. For both fixed effects estimators however, reallocation shares are much larger, although still positive. The De Loecker estimator allowing for variety-specific demand, as well as the LP estimator yield a small but consistently negative sample covariance term between productivity and either output or employment.

5 Conclusions

This paper has reviewed the methodological issues arising when total factor productivity or TFP is estimated at the establishment level. The traditional biases introduced by the simultaneity of input choice and endogeneity of attrition have been discussed; as well as a number of issues that have emerged more recently, i.e. related to imperfect competition in input and/or output markets and endogeneity of product choice. Various estimators have been introduced in the literature attempting to overcome some of these issues.

Method	Turnover shares Weighted Index (1996 = 1)(1)	Turnover shares Mean TFP (2) (%)	Turnover shares Reallo-cation (%) (2)	Employment shares Weighted Index (1996 = 1)(1)	Employment shares Mean TFP (2) (%)	Employment shares Reallo-cation (%) (2)
OLS	1.1393	99.24	0.76	1.1606	99.39	0.61
Fixed Effects (balanced)	1.1619	92.18	7.82	1.1773	84.58	15.42
Fixed Effects (unbalanced)	1.1657	90.42	9.58	1.1787	81.53	18.47
GMM	1.1453	98.52	1.48	1.1686	96.44	3.56
OP (no survival correction)	1.1377	99.45	0.55	1.1582	99.57	0.43
OP (survival correction)	1.1375	99.48	0.52	1.1580	99.64	0.36
Levinsohn-Petrin	1.1293	101.68	-1.68	1.1504	105.08	-5.08
De Loecker	1.1148	97.74	2.26	1.1613	96.62	3.38
DL (variety-specific)	1.0323	101.15	-1.15	1.0855	102.86	-2.86

Weighted average productivity is calculated as in equation 17, weights are firm-level turnover of employment shares. (1) Weighted normalized TFP in 2003 (1996 = 1). (2) Values reported are eight-year averages of the shares of unweighted average TFP and the sample covariance term.

Table 7: Comparison of decomposition results

Given the relatively poor performance and shortcomings of the more traditional estimators, i.e. fixed effects and GMM; a number of semiparametric estimators have been introduced, which have been briefly reviewed here. A recent extension to these estimators taking the omitted output price bias into account; in addition to dealing adequately with simultaneity and selection issues has also been discussed.

I have illustrated the performance of these estimators using data on the food and beverages industry in Belgium in the period 1996 to 2003, when the sector was undergoing significant changes and restructuring, especially following the outbreak of the dioxin crisis in 1999. Findings confirm the theoretically expected biases in traditional production function estimates, obtained using OLS. Moreover, the evolution of industry TFP over the sample period shows a clear upward trend in aggregate productivity following the dioxin scandal in 1999.

Which estimator would researchers ideally want to use then? In light of the traditionally poor performance of both the GMM and fixed effects estimators, it would seem that the semiparametric estimators are to be preferred, and specifically the Olley-Pakes methodology. Moreover, comparing aggregate industry productivity growth patterns for the different estimators shows that a failure to take imperfect competition in output markets into account may yield misleading results concerning the timing and magnitude of observed industry growth patterns, hence favoring the estimator of De Loecker.

However, the choice of which estimator to use will essentially also depend on the data at hand. Reliable industry output measures are not always available to the researcher. Similarly, positive investment data are not always available for a sufficiently large sample of firms within an industry or might not be trustworthy. Data can also be prone to measurement error or production technology may differ widely within an industry, invalidating some of the parametric methods discussed here.

Van Biesebroeck (2007) compares the sensitivity of different estimators (index numbers, data envelopment analysis or DEA, stochastic frontiers, IV (GMM) and semiparametric estimation. He finds that the GMM-SYS estimator is the most robust technique when there is a lot of measurement error or some technological heterogeneity. However, for the GMM-SYS estimator to be reliable, at least some of the productivity differences have to be constant over time. He further notes that the GMM estimator might lead to downwardly biased input coefficients when measurement error becomes severe. When measurement error is small, technology is heterogeneous and returns to scale are not constant, non-parametric techniques such as DEA or index numbers should be preferred.

In spite of the multitude of estimators that have been developed in recent years in order to achieve consistent estimates of total factor productivity, a number of issues remain to be resolved. In particular, both the lack of a formal correction for the omitted input price bias in the presence of imperfect competition in input markets, as well as the implications of endogenous product choice following from BRS (2005, 2006b) offer ample scope for future research.

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