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Production function estimation in Stata using the Ackerberg–Caves–Frazer method

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Abstract. We present a new e-class command, `acfest`, that implements the method of Ackerberg, Caves, and Frazer (2015, *Econometrica* 83: 2411–2451) to estimate production functions. This method deals with the functional dependence problems that may arise in the methods proposed by Olley and Pakes (1996, *Econometrica* 64: 1263–1297) and, particularly, Levinsohn and Petrin (2003, *Review of Economic Studies* 70: 317–341) (implemented in Stata by Yasar, Raciborski, and Poi [2008, *Stata Journal* 8: 221–231] and Petrin, Poi, and Levinsohn [2004, *Stata Journal* 4: 113–123], respectively). In particular, the `acfest` command yields (nonlinear, robust) generalized method of moments estimates using a Mata function and two specification tests (Wald and Sargan–Hansen). After estimation, `predict` provides the estimated productivity of the firms in the sample.

Keywords: st0460, acfest, endogeneity, generalized method of moments, levpet, opreg, production functions

1 Introduction

Estimation of the parameters of a production function is key in many areas of economics. Industrial organization is of course the prominent example, because this is one of the main empirical tools for analyzing market outcomes (Ackerberg et al. 2007). But the use of production functions is not uncommon in empirical studies in international economics (for example, Pavcnik [2002]), environmental economics (for example, Koźluk and Zipperer [2015]), and development economics (for example, Göbel, Grimm, and Lay [2012]). At the macrolevel, production function estimates from microdata are typically used to construct aggregates. Petrin and Levinsohn (2012), for example, have recently shown how to use plant-level estimates by industry to estimate the aggregate productivity growth of an economy.

 st0460

However, consistent estimation of the parameters of a production function can be rather involved (Marschak and Andrews 1944). If firms optimally choose the level of inputs consumed in the production process (that is, as the solution of a dynamic profit maximization problem), then inputs are likely to be endogenous variables because the error term of the model typically contains output determinants that are observed by the firm but not by the analyst (notably, the firm's productivity). This means that standard estimation methods such as ordinary least squares (OLS) yield inconsistent estimates. Also, more elaborate methods, such as the (instrumental variables) within-groups or fixed-effects estimator, do not seem to work well either (Griliches and Mairesse 1998).

To control for the correlation between the unobservable productivity shocks and the input levels, Olley and Pakes (1996) proposed using a firm's investment as a proxy variable for a firm's productivity and a low-order polynomial to approximate the (unknown) control function.[1] When firms face substantial adjustment costs, however, the investment variable may not be appropriate (it may not fully respond to changes in productivity, and it may become severely truncated at zero). This led Levinsohn and Petrin (2003) to propose an alternative approach that uses intermediate inputs rather than investments in the control function. This approach is not just potentially more efficient but, because of the difficulties to obtain information on firm-level investment, often the only one available.

Yet Ackerberg, Caves, and Frazer (2015) argue that these estimation strategies—particularly, the one advocated by Levinsohn and Petrin (2003)—may suffer from identification issues. These authors show that unless additional assumptions are made about the data-generating processes, the labor input may not vary independently of the nonparametric function that is being estimated using the low-order polynomial. Further, to avoid this functional dependence problem, Ackerberg, Caves, and Frazer (2015) propose an estimation procedure that draws on aspects of both the Olley and Pakes (1996) and Levinsohn and Petrin (2003) two-stage procedures but that estimates all the input coefficients (that is, including the labor coefficient) in the second stage.[2]

Yasar, Raciborski, and Poi (2008) implemented the Olley and Pakes (1996) procedure in Stata, whereas Petrin, Poi, and Levinsohn (2004) did the same for the Levinsohn and Petrin (2003) procedure. However, to date, the proposal by Ackerberg, Caves, and Frazer (2015) is not available in Stata. In this article, we discuss its implementation as a new e-class command named `acfest`. In particular, the rest of the article is set out as follows. Section 2 reviews the relevant theory, section 3 discusses the syntax of the `acfest` command, and section 4 illustrates the use of `acfest` using data on Spanish manufacturing firms. Section 5 concludes.

1. Olley and Pakes (1996) also discuss how to address the sample selection bias arising from the endogeneity of the exit decision (see Ackerberg et al. [2007, footnote 34] for a brief discussion of the conditions under which this bias arises). In applications, however, evidence provided by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Van Beveren (2012) suggests that the selection bias is much less important than the simultaneity bias. In any case, the `opreg` command of Yasar, Raciborski, and Poi (2008) provides a simple procedure to control for this bias.
2. All of these methods bootstrap the standard errors to avoid deriving their complex analytical expressions. In contrast, Wooldridge (2009) proposes a potentially more efficient one-step approach that enables the standard errors to be estimated directly.

2 Estimating production functions

In this section, we first lay out the model specification and then the main assumptions that sustain the method proposed by Olley and Pakes (1996). We do so using a general framework in which the proposals of Levinsohn and Petrin (2003), Wooldridge (2009), and Ackerberg, Caves, and Frazer (2015) are embedded. Next, we describe the estimation procedure and point out the main differences between the methods proposed by these authors. We conclude with the details of the method proposed by Ackerberg, Caves, and Frazer (2015).[3]

2.1 Model specification

Let us assume that a firm's production technology can be represented by a production function $f(\cdot)$ that relates output (Y), inputs ($\mathbf{X} = [X^1, X^2, \ldots]$), and the (Hicksian neutral) efficiency level of the firm (A), so that $Y = f(Y, \mathbf{X}, A)$. Also, let us assume that firms produce a homogeneous good using a Cobb–Douglas technology,[4]

$$y_{jt} = \beta_0 + \sum_k \beta_k x_{jt}^k + \omega_{jt} + \eta_{jt} \tag{1}$$

where y_{jt} and x_{jt}^k denote the log of output (value added or gross revenue) and the log of the k input for firm j at period t, respectively, $\ln(A_{jt}) = \beta_0 + \varepsilon_{jt}$, and $\varepsilon_{jt} = \omega_{jt} + \eta_{jt}$.[5] In this vein, (1) has two unobservables: the log of a firm's productivity (ω_{jt}) and a residual (η_{jt}) that is assumed to have the standard properties.[6]

3. The contents of this section are based on the work of Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015), and Ackerberg et al. (2007). See also Van Beveren (2012) for a recent survey of the production function literature and Griliches and Mairesse (1998) for a historical account. Petrin, Poi, and Levinsohn (2004) and Yasar, Raciborski, and Poi (2008) provide an analysis of the estimation of production functions using Stata (the commands `levpet` and `opreg`, respectively).
4. Although the Cobb–Douglas technology is the most commonly assumed, other production technologies may be considered as long as they satisfy certain conditions —see, for example, Olley and Pakes (1996, footnote 18) and Ackerberg et al. (2007, footnote 14) for details.
5. We follow the usual practice in this literature of denoting a variable in levels with uppercase letters and the log of a variable with lowercase letters.
6. "The constant term β_0 can be interpreted as the mean efficiency level across firms, while ε_j is the deviation from that mean for firm j", that is, ε_j "might represent innate technology or management differences between firms, measurement errors in output, or unobserved sources of variance in output caused by weather, machine breakdowns, labor problems, etc." Further, "ω_j might represent factors like managerial ability at a firm, expected down-time due to machine breakdowns or strikes, or the expected rainfall at a farm's location". Lastly, "η_j might represent deviations from expected breakdown rates in a particular year or deviations from expected rainfall at a farm" (Ackerberg et al. 2007, 4205–4207).

Typically, output and inputs are observable by both the firm and the analyst; productivity is observed only by the firm; and the error term is not observable, either by the firm or by the analyst. This is why the correlation between labor and productivity renders OLS estimates of (1) biased and inconsistent (Marschak and Andrews 1944). Also, standard approaches to endogeneity, such as the fixed-effects or within-groups estimator and the instrumental-variable method do not work (Griliches and Mairesse 1998). The fixed-effects estimator may deal with the labor-productivity correlation but at the cost of imposing productivity shocks with no time variation. Similarly, instrumental-variable methods are limited by the difficulty of finding appropriate instruments (that is, variables that are correlated with the endogenous variable but uncorrelated with the productivity term).

2.2 Assumptions

Rather than resorting to (flawed) standard estimation methods, one can derive the identification of (1) from "a dynamic model of firm behavior that [allows for] 'idiosyncratic uncertainty' [and specifies] the information available when input decisions are made" (Olley and Pakes 1996, 1271). This amounts to assuming that firms make decisions to maximize the present discounted value of current and future profits in an environment in which productivity is the (only unobserved) source of firm-specific uncertainty. In particular, it is assumed that ω_{jt} follows an exogenous first-order Markov process. Also, the solution to the dynamic profit maximization problem generates a demand function for the proxy variable (investment in Olley and Pakes 1996, intermediate materials in Levinsohn and Petrin 2003) that, under certain assumptions, can be inverted to define a firm's productivity as a function of observables (the control function). These assumptions are of two types: the first relates to the inputs and the second to the control function.

First, inputs are assumed to differ in two fundamental dimensions: whether their current choice affects their cost in future periods (that is, their "dynamic nature") and whether the time period they are chosen for is the period in which they are used in the production process (that is, their "timing"). With respect to their dynamic nature, we can distinguish two types of input: those whose choice in the current period does not have an impact on their cost of use in future periods (nondynamic inputs, including labor and intermediate inputs, such as materials and energy) and those whose current choice does have an impact on the future cost of input use (dynamic inputs, such as capital and age, whose current value becomes a "state variable" of the firm's dynamic profit-maximization problem). As far as the timing is concerned, we can distinguish two types of input: those that are chosen in the same period as they are consumed (free or variable inputs, such as labor, materials, and energy) and those that are chosen before the period they are consumed (fixed inputs, such as capital and, by nature, age).

Thus, if we denote $\mathbf{w}_{jt}$ as the vector of variable inputs and $\mathbf{s}_{jt}$ as the vector of state variables, then we can rewrite (1) as

$$y_{jt} = \beta_0 + \boldsymbol{\beta}_w \mathbf{w}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + \omega_{jt} + \eta_{jt} \tag{2}$$

where $\boldsymbol{\beta}_w$ and $\boldsymbol{\beta}_s$ are parameter vectors of the appropriate dimension. Labor is usually the only component of $\mathbf{w}_{jt}$ in the value-added case (that is, when y_{jt} is gross-output net of intermediate inputs; see, for example, Olley and Pakes [1996]). When the output is measured as (gross) revenue, however, the vector of variable inputs is typically made up of labor and some intermediate inputs (Levinsohn and Petrin 2003, for example, consider materials, fuels, and electricity).

Second, the demand function for the proxy variable, $d_{jt}(\cdot)$, is assumed to have a single unobservable among its arguments (scalar unobservable assumption) and to be strictly monotonic in the unobserved productivity (monotonicity assumption). Thus, given that in equilibrium the demand function depends only on state variables, we can write the proxy demand function as $d_{jt} = d_t(\mathbf{s}_{jt}, \omega_{jt})$. Also, conditional on the observed state variables, "profit maximizing behavior must lead more productive firms to use" the proxy variable more (positive investment in Olley and Pakes 1996, intermediate materials in Levinsohn and Petrin 2003, 322).

Interestingly, under the scalar unobservable and monotonicity assumptions, the demand function for the proxy variable can be inverted to generate

$$\omega_{jt} = d_t^{-1}(\mathbf{s}_{jt}, \omega_{jt}) = h_t(\mathbf{s}_{jt}, d_{jt}) \tag{3}$$

2.3 Estimation procedure

First stage

We plug the inverse of the demand function for the proxy variable (3) into the production function (2) to obtain

$$\begin{aligned} y_{jt} &= \beta_0 + \boldsymbol{\beta}_w \mathbf{w}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + h_t(\mathbf{s}_{jt}, d_{jt}) + \eta_{jt} \\ &= \boldsymbol{\beta}_w \mathbf{w}_{jt} + \phi_t(\mathbf{s}_{jt}, d_{jt}) + \eta_{jt} \end{aligned} \tag{4}$$

where $\phi_t(\cdot)$ is an unknown function that combines β_0, $\boldsymbol{\beta}_s \mathbf{s}_{jt}$, and $h_t(\mathbf{s}_{jt}, d_{jt})$. Notice that we now "observe the unobserved ω_{jt}" (Ackerberg et al. 2007, 4215). Thus, there is no endogeneity problem. Also, estimation using semiparametric methods avoids specifying the demand function for the proxy variable (which can be rather involved because $d_{jt}(\cdot)$ ultimately depends on all the primitives of a dynamic model of firm behavior). Olley and Pakes (1996), for example, use low-order polynomials to approximate $\phi_t(\cdot)$, whereas Levinsohn and Petrin (2003) use a locally weighted quadratic least-squares approximation.

The downside is that not all the parameters of (2) are identified. To be precise, the function $\phi_t(\cdot)$ is identified regardless of the proxy and output variables we use, but the identification of the variable input coefficients depends on the proxy and output variables we use. In the value-added case and regardless of the proxy variable used (investment or materials), only the labor coefficient is identified (Olley and Pakes 1996; Petrin, Poi, and Levinsohn 2004). In the revenue case, only the labor coefficient is identified when materials are used (in general, an intermediate input) as a proxy variable

(Levinsohn and Petrin 2003), whereas all the variable input coefficients are identified when investment is used as a proxy variable (Yasar, Raciborski, and Poi 2008).[7] Thus, if required, the state variable coefficients, $\boldsymbol{\beta}_s$, firm's productivity, ω_{jt}, and the nonidentified variable input coefficients—which we denote $\boldsymbol{\beta}_{w^{\mathrm{NI}}}$, so that, in obvious notation to distinguish identified and nonidentified coefficients, $\boldsymbol{\beta}_w = [\boldsymbol{\beta}_{w^{\mathrm{I}}}, \boldsymbol{\beta}_{w^{\mathrm{NI}}}]$—must be estimated in a second stage.

Second stage

Given the exogenous first-order Markov process assumption and that $\phi_t(\mathbf{s}_{jt}, d_{jt}) = \beta_0 + \boldsymbol{\beta}_s \mathbf{s}_{jt} + \omega_{jt}$ (a result derived from the first stage), decomposing firms' productivity into its conditional expectation at time $t-1$ and a deviation from that expectation produce

$$\omega_{jt} = E(\omega_{jt} \mid \omega_{j,t-1}) + \xi_{jt} = g(\omega_{j,t-1}) + \xi_{jt} = g(\phi_{t-1} - \beta_0 - \boldsymbol{\beta}_s \mathbf{s}_{j,t-1}) + \xi_{jt} \tag{5}$$

We then plug (5) into (2) to obtain

$$y_{jt} = \beta_0 + \boldsymbol{\beta}_w \mathbf{w}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + g(\phi_{t-1} - \beta_0 - \boldsymbol{\beta}_s \mathbf{s}_{j,t-1}) + \xi_{jt} + \eta_{jt} \tag{6}$$

Notice that ξ_{jt} is orthogonal to the state variables but not to the variable inputs (the firm observes its productivity at the time the variable input is chosen). Thus (6) identifies the state variable coefficients and the firm's productivity when investment is used as a proxy. However, we must account for the correlation between the ξ_{jt} and the variable inputs when intermediate inputs are used as proxy variables.

In any case, the estimation procedure is analogous (and does not identify β_0, so we use below a new function $\widetilde{g}$ to account for this). The key is to replace ϕ_{t-1} by its first-stage estimate, $\widehat{\phi}_{t-1}$, and use the first-stage estimates of the variable input coefficients identified in the first stage, $\widehat{\boldsymbol{\beta}}_{w^{\mathrm{I}}}$, to construct a new dependent variable $y^*_{jt} = y_{jt} - \widehat{\boldsymbol{\beta}}_{w^{\mathrm{I}}} \mathbf{w}^{\mathrm{I}}_{jt}$. The resulting model,

$$y^*_{jt} = \boldsymbol{\beta}_{w^{\mathrm{NI}}} \mathbf{w}^{\mathrm{NI}}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + \widetilde{g}\left(\widehat{\phi}_{t-1} - \boldsymbol{\beta}_s \mathbf{s}_{j,t-1}\right) + \xi_{jt} + \eta_{jt}$$

can then be estimated using, for example, a low-order polynomial approximation for $\widetilde{g}(\cdot)$. Notice that $\mathbf{w}^{\mathrm{NI}}$ (the vector of variable input coefficients that are not identified in the first stage) is typically empty in the value-added case and when investment is used as a proxy. Thus a nonlinear least-squares estimator may suffice to achieve consistency (Olley and Pakes 1996; Yasar, Raciborski, and Poi 2008).[8] However, if intermediate inputs are used as a proxy in the revenue case, $\mathbf{w}^{\mathrm{NI}}$ typically contains the

7. Actually, identification of the variable input coefficients may require additional (and possibly strong and implausible) conditions—see, for example, Bond and Söderbom (2005) and Ackerberg, Caves, and Frazer (2015).
8. Alternatively, one may use a (kernel) regression of $y^*_{jt} - \boldsymbol{\beta}_{w^{\mathrm{NI}}} \mathbf{w}^{\mathrm{NI}}_{jt} - \boldsymbol{\beta}_s \mathbf{s}_{jt}$ on $\widehat{\omega}_{j,t-1} = \widehat{\phi}_{t-1} - \boldsymbol{\beta}_s \mathbf{s}_{j,t-1}$ and a nonlinear search algorithm to find the value of $\boldsymbol{\beta}_s$ (and $\boldsymbol{\beta}_{w^{\mathrm{NI}}}$) that minimizes the sum of the squared residuals from this regression (Olley and Pakes 1996, 1279).

intermediate inputs that are used as proxy variables (d_{jt}). Also, a generalized method of moments estimator must be used to control for the endogeneity of $\mathbf{w}^{\rm NI}$. In particular, Levinsohn and Petrin (2003) propose using moments based on the orthogonality between ξ_{jt} and the state variables and lags of the variable inputs to construct additional overidentifying conditions,[9]

$$E\left\{(\xi_{jt}+\eta_{jt})\left(\begin{array}{c}\mathbf{s}_{jt}\\ \mathbf{w}^{\rm NI}_{j,t-1}\end{array}\right)\right\}=0 \tag{7}$$

where $\xi_{jt}+\eta_{jt} = y^*_{jt} - \boldsymbol{\beta}_{w^{\rm NI}}\mathbf{w}^{\rm NI}_{jt} - \boldsymbol{\beta}_s\mathbf{s}_{jt} - E(\widehat{\omega_{jt} \mid \omega_{j,t-1}})$ and $E(\widehat{\omega_{jt} \mid \omega_{j,t-1}})$ is obtained from the prediction of a (locally weighted) regression between $\widehat{\omega_{jt}+\eta_{jt}} = y^*_{jt} - \boldsymbol{\beta}_{w^{\rm NI}}\mathbf{w}^{\rm NI}_{jt} - \boldsymbol{\beta}_s\mathbf{s}_{jt}$ and $\widehat{\omega}_{j,t-1} = \widehat{\phi}_{t-1} - \boldsymbol{\beta}_s\mathbf{s}_{j,t-1}$.[10]

2.4 The Ackerberg, Caves, and Frazer (2015) method

The main argument in Ackerberg, Caves, and Frazer (2015) is that the labor coefficient may not be identified in the estimation procedures proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). If labor is actually a state variable (because of the existence of significant hiring and firing costs and long-term contracts, which occurs in such European countries as Spain), then labor should be an argument of the demand function of the proxy variable in (3) and the function $\phi_t(\cdot)$ in (4). Thus, if l denotes the labor input, these functions should now be defined as $\omega_{jt} = h_t(s_{jt}, d_{jt}, l_{jt})$ and $\phi_t(s_{jt}, d_{jt}, l_{jt})$, respectively. This prevents the labor coefficient from being identified in the first stage (and, in general, any variable input whose current choices have an impact on its future cost). However, Ackerberg, Caves, and Frazer (2015) show that this parameter, along with all the other input coefficients, can be identified in the second stage of the procedure. Next, we describe in detail the estimation procedure they propose.

First stage

We plug the inverse of the demand function for the proxy variable into the production function:

$$y_{jt} = \beta_0 + \boldsymbol{\beta}_w\mathbf{w}_{jt} + \boldsymbol{\beta}_s\mathbf{s}_{jt} + h_t(s_{jt}, d_{jt}, l_{jt}) + \eta_{jt}$$

Notice that in contrast to the first stage of Olley and Pakes (1996) and Petrin, Poi, and Levinsohn (2004), none of the coefficients are identified. That is, $\mathbf{w} \equiv \mathbf{w}^{\rm NI}$. However, "we still need the first stage to generate estimates of $\widehat{\phi}_{t-1}$", which helps us to approximate the unobserved productivity (Ackerberg et al. 2007, 4223). In particular,

9. One may of course exploit additional overidentifying moment conditions based on the lags of $\mathbf{s}_{jt}$ and $\mathbf{w}_{j,t-1}$.
10. In the value-added case with capital as the only state variable and materials as the proxy variable, Petrin, Poi, and Levinsohn (2004) use a golden section line-search algorithm to find the value of the capital coefficient that minimizes the sum of the squared residuals, $\sum_j \sum_t (\xi_{jt}+\eta_{jt})^2$.

Ackerberg, Caves, and Frazer (2015) use the first stage of the procedure to obtain an estimate of the composite term,

$$\Phi_t(\mathbf{w}_{jt}, \mathbf{s}_{jt}, d_{jt}) = \beta_0 + \boldsymbol{\beta}_w \mathbf{w}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + h_t(\mathbf{s}_{jt}, d_{jt}, l_{jt})$$

Second stage

With this estimate, $\widehat{\Phi}_t(\mathbf{w}_{jt}, \mathbf{s}_{jt}, d_{jt})$, we can now estimate all the parameters of interest using the following equation:

$$y_{jt} = \beta_0 + \boldsymbol{\beta}_w \mathbf{w}_{jt} + \boldsymbol{\beta}_s \mathbf{s}_{jt} + \widetilde{g}\left(\widehat{\Phi}_{t-1} - \beta_0 - \boldsymbol{\beta}_w \mathbf{w}_{j,t-1} - \boldsymbol{\beta}_s \mathbf{s}_{j,t-1}\right) + \xi_{jt} + \eta_{jt}$$

Note that in the value-added case, $\mathbf{w}_{jt}$ includes only labor (l_{jt}), whereas the revenue case typically also contains a vector of $\mathbf{m}$ intermediate inputs. An interesting case is the revenue case when an intermediate input is used as proxy: then $\mathbf{w}_{jt}$ includes labor, the proxy variable (d_{jt} contains an intermediate input), and a vector of the $\mathbf{m}-1$ remaining intermediate inputs.

In any case, the presence of l_{jt} in $\mathbf{w}$ means that ξ_{jt} and $\mathbf{w}$ are no longer orthogonal. Thus, compared with the Olley and Pakes (1996) and Petrin, Poi, and Levinsohn (2004) moment condition in (7), an additional moment condition is now needed to identify the labor coefficient. Lagged variable inputs are natural candidates for this, so the proposed generalized method of moments estimator uses the sample analog of

$$E\left\{(\xi_{jt} + \eta_{jt})\begin{pmatrix} \mathbf{s}_{jt} \\ \mathbf{w}_{j,t-1} \end{pmatrix}\right\} = 0$$

Needless to say, additional (overidentifying) conditions can be obtained by considering, for example, powers and lags of $\mathbf{s}_{jt}$ and $\mathbf{w}_{j,t-1}$. Yet, users should be aware of the identification problems that may arise in this approach when estimating revenue functions that include intermediate inputs in $\mathbf{w}_{jt}$. In fact, as shown by Bond and Söderbom (2005) (for the Cobb–Douglas case) and Gandhi, Navarro, and Rivers (2013) (for the general case), under the scalar unobservable assumptions of Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015), there is no guarantee that these gross-output production functions are identified. This is why Ackerberg, Caves, and Frazer (2015) recommend that their method be used only with value-added production functions in which the intermediate input m_{jt} does not enter the production function. Notice, however, that this amounts to assuming that either the gross-output production function is Leontief in the intermediate input (that is, the intermediate input is proportional to the output) or that there exists a "meaningful value-added production function" (see, for example, Basu and Fernald 1997 for details).

3 The acfest command

3.1 Syntax

`acfest` *depvar* [*if*] [*in*] , `free(`*varlist*`)` `state(`*varlist*`)` `proxy(`*varname*`)`
[`i(`*varname*`)` `t(`*varname*`)` `intmat(`*varlist*`)` `invest` `nbs(`*#*`)` `robust` `nodum`
`second` `va` `overid`]

where *depvar* is the dependent variable (revenue is the default; value added is used when the `va` option is specified). *depvar*, `free()`, `state()`, `proxy()`, `i()`, `t()`, and `intmat()` may contain time-series operators. `free()` contains the list of labor inputs (for example, white-collar and blue-collar workers); `state()` contains the list of state variables (for example, capital and age); and `proxy()` is the proxy variable (typically, investment or intermediate materials). `free()`, `state()`, and `proxy()` are required. Also, by typing the appropriate term, the user can specify the use of investment as a proxy, `invest` (materials is the default). Similarly, in the revenue case, the user must specify `intmat()`, the list of intermediate inputs when investment is used as a proxy, whereas when the demand of an intermediate input is used as a proxy, the user can optionally include intermediate materials other than the one used as a proxy in `intmat()` (for example, fuels and electricity). Lastly, notice that all of these variables should be in logs and that data in memory must have been declared as panel; otherwise, the user must identify both the panel variable, `i(`*varname*`)`, and the time variable, `t(`*varname*`)`.

To illustrate the full capabilities of `acfest`, let's consider a user handling a dataset containing firm-level information on revenue (`y`); value added (`va`); investment(`inv`); blue- and white-collar labor ($\mathtt{l}_b$ and $\mathtt{l}_w$, respectively); information and communication technologies (ICT) and non-ICT capital ($\mathtt{k}_{\mathrm{ICT}}$ and `k`, respectively); age (`a`); and three intermediate inputs (materials, electricity, and fuel, which we denote `m`, `e`, and `f`, respectively). Table 1 summarizes the basic syntax of `acfest` for the revenue and value-added cases, using both investment and intermediate inputs as proxies.

Table 1. Basic syntax of the `acfest` command

	`state()`	`free()`	`proxy()`	`intmat()`	`va`	`invest`
Value-added investment	`k`, $\mathtt{k}_{\mathrm{ICT}}$, `a`	$\mathtt{l}_w$, $\mathtt{l}_b$	`inv`		yes	yes
Value-added materials	`k`, $\mathtt{k}_{\mathrm{ICT}}$, `a`	$\mathtt{l}_w$, $\mathtt{l}_b$	`m`		yes	
Revenue investment	`k`, $\mathtt{k}_{\mathrm{ICT}}$, `a`	$\mathtt{l}_w$, $\mathtt{l}_b$	`inv`	`m`, `e`, `f`		yes
Revenue materials	`k`, $\mathtt{k}_{\mathrm{ICT}}$, `a`	$\mathtt{l}_w$, $\mathtt{l}_b$	`m`	`e`, `f`		

The options also allow the user to determine the number of replications used in bootstrapping (the default is `nbs(100)`); to obtain standard errors robust to arbitrary heteroskedasticity (`robust`, with independent and identically distributed errors assumed by default); not to include time dummies in the (first-stage) estimation of ϕ, `nodum` (time dummies are included by default); to use a second-order polynomial to construct the control function, `second` (a third-order polynomial is the default); and to consider the following additional instruments: 1) `overid` uses the lag of the state variables and the second lag of the labor variables in the value-added case (the default is to use the state and lagged labor inputs); and 2) it uses the lag of the state variables and the second lag of the full set of variable inputs in the revenue case (the default is to use the state and the full set of lagged variable inputs).

3.2 Syntax for predict after acfest

`predict` *newvar* [*if*] [*in*], `omega`

where *newvar* is the name of the variable that will contain the estimated (log) productivity, $\widehat{\omega}_{jt}$. `omega` specifies the estimated productivity and is required. In particular, the new variable is generated as $y_{jt} - \widehat{\boldsymbol{\beta}}_w \mathbf{w}_{jt} - \widehat{\boldsymbol{\beta}}_s \mathbf{s}_{jt}$ using the estimated coefficients obtained from `acfest`.

3.3 Stored results

`acfest` stores the following results in `e()`:

Scalars

`e(N)`	number of observations	`e(waldcrs)`	Wald test statistic of constant returns to scale
`e(L)`	number of instruments		
`e(K)`	number of exogenous variables	`e(j)`	Sargan–Hansen test statistic

Macros

`e(depvar)`	name of the dependent variable	`e(predict)`	program used to implement `predict`
`e(vcetype)`	`robust`		

Matrices

`e(b)`	coefficient vector	`e(V)`	variance–covariance matrix of the estimators

Functions

`e(sample)`	marks estimation sample

4 Examples

We use data on Spanish manufacturing firms drawn from the Encuesta sobre Estrategias Empresariales to illustrate the `acfest` command. The Encuesta sobre Estrategias Empresariales is an annual survey sponsored by the Spanish Ministry of Industry and has been carried out since 1990. It is representative of Spanish manufacturing firms classified by industrial sectors and size categories.[11] In particular, we use the dataset constructed by Manjón et al. (2013) to analyze the relation between exports and pro-

11. More information about this survey can be found at http://www.funep.es/esee/en/einfo_que_es.asp.

ductivity. More specifically, we selected the 457 firms that provided data for all the variables of interest (revenue, value added, labor, capital, age, intermediate materials, and exports) for the period 1993 to 2005.

We start with the most basic syntax using capital (`k`) and age (`a`) as state variables, intermediate materials (`m`) as a proxy, and labor (`l`) as the free input. Among the available options, we identify the panel (`firm`) and time (`year`) variables, and specify the number of bootstrap replications (200). We report results for both revenue (`y`) and value added (`va`) as dependent variables. We also report OLS estimates for comparative purposes.

The coefficient estimates we obtain are largely consistent with those reported in the literature (see, for example, Van Beveren [2012]). In particular, when one controls for the endogeneity of the variable inputs, changes in the value of the coefficients all go in the right direction. This means that compared with the OLS estimates of the revenue function, the values for the labor and materials coefficients are lower, and the values for the capital coefficient (only in the revenue specification) are higher. Also note that whereas we reject the null hypothesis of constant returns to scale in the revenue specification, we do not reject it in the value-added specification. Lastly, because in both cases the model is exactly identified, we cannot test for overidentifying restrictions. The Sargan–Hansen test reflects this by providing the test statistic but not the p-value.

```
. acfest y, state(k a) proxy(m) free(l) i(firm) t(year) nbs(200)
.......................................................................
> ......................................................................
> ......................................................
Ackerberg-Caves-Frazer Method to Estimate Production Functions
(Non-linear homoskedastic GMM estimates for revenue)
                                                        Number of obs = 5484
------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .1161491   .0192382     6.04   0.000      .078443    .1538553
           a |   .0403692   .0166019     2.43   0.015     .0078301    .0729082
           m |     .61435   .0664836     9.24   0.000     .4840446    .7446554
           l |   .2554177    .062227     4.10   0.000     .1698339    .4137594
------------------------------------------------------------------------------
Wald test of constant returns to scale: Chi2 =  27.88 (p = 0.0000)
Sargan-Hansen J-statistic:   2.502 (p = .)
Exactly identifided model (no overidentifying restrictions)
```

```
. regress y k a m l if e(sample)
      Source |       SS           df       MS      Number of obs   =     5,484
-------------+----------------------------------   F(4, 5479)      =  75350.49
       Model |  19076.8401         4  4769.21002   Prob > F        =    0.0000
    Residual |  346.786111     5,479  .063293687   R-squared       =    0.9821
-------------+----------------------------------   Adj R-squared   =    0.9821
       Total |  19423.6262     5,483    3.542518   Root MSE        =    .25158

------------------------------------------------------------------------------
           y |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .1092515   .0041902    26.07   0.000      .101037     .117466
           a |   .0681793   .0055994    12.18   0.000     .0572022    .0791564
           m |   .6368476   .0044021   144.67   0.000     .6282178    .6454774
           l |   .2624117   .0061232    42.86   0.000     .2504077    .2744157
       _cons |   2.974325   .0400657    74.24   0.000      2.89578     3.05287
------------------------------------------------------------------------------

. acfest va, state(k a) proxy(m) free(l) i(firm) t(year) nbs(200) va
..........................................................................
> .........................................................................
> ..................................................
Ackerberg-Caves-Frazer Method to Estimate Production Functions
(Non-linear homoskedastic GMM estimates for value added)
                                                          Number of obs = 5484
------------------------------------------------------------------------------
          va |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .2255843   .1113753     2.03   0.043     .0072928    .4438759
           a |   .0452443   2.896705     0.02   0.988    -5.632194    5.722682
           l |   .6891031   .2565605     2.69   0.007     .1862537    1.191952
------------------------------------------------------------------------------
Wald test of constant returns to scale: Chi2 =   0.00 (p = 0.9890)
Sargan-Hansen J-statistic:   0.038 (p = .)
Exactly identifided model (no overidentifying restrictions)
. regress va k a l if e(sample)
      Source |       SS           df       MS      Number of obs   =     5,484
-------------+----------------------------------   F(3, 5480)      =  22610.21
       Model |  16856.7069         3  5618.90231   Prob > F        =    0.0000
    Residual |  1361.84416     5,480  .248511708   R-squared       =    0.9252
-------------+----------------------------------   Adj R-squared   =    0.9252
       Total |  18218.5511     5,483   3.3227341   Root MSE        =    .49851

------------------------------------------------------------------------------
          va |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |    .304464   .0073308    41.53   0.000     .2900927    .3188354
           a |   .0901184   .0110719     8.14   0.000     .0684131    .1118238
           l |   .7699258   .0108193    71.16   0.000     .7487158    .7911359
       _cons |   6.389548   .0614492   103.98   0.000     6.269083    6.510013
------------------------------------------------------------------------------
```

Next, we consider using investment (`i`) as a proxy in the revenue specification and specify the `robust` option to obtain robust standard errors. Then, we show the effects of using the `second` option: that is, we use a second-order polynomial to construct the control function (rather than the third-order polynomial used by default). The first thing to notice is that using investment rather than materials has a larger impact on the variable inputs' coefficients (materials and labor) than on the state coefficients (capital and age). Second, using a second- rather than a third-order polynomial has a similar impact on the coefficients, which means that they are now closer to those obtained using intermediate materials as a proxy. Also note that we reject the null hypothesis of constant returns to scale (both for the revenue and value-added specification), and because the model is exactly identified, we cannot test for overidentifying restrictions.

```
. acfest y, state(k a) proxy(i) free(l) i(firm) intmat(m) t(year) nbs(200)
> invest robust
........................................................................
> .......................................................................
> ..................................................
Ackerberg-Caves-Frazer Method to Estimate Production Functions
(Non-linear heteroskedastic GMM estimates for revenue)
                                                         Number of obs = 5484

             |               robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .1069995   .0138518     7.72   0.000     .0798505    .1341485
           a |   .1010313   .0139767     7.23   0.000     .0736375    .1284251
           m |   .7372477   .0199144    37.02   0.000     .6982162    .7762792
           l |   .1452563   .0163867     8.86   0.000     .1131391    .1773736

Wald test of constant returns to scale: Chi2 =  72.36 (p = 0.0000)
Sargan-Hansen J-statistic:   0.000 (p = .)
Exactly identifided model (no overidentifying restrictions)
. acfest y, state(k a) proxy(i) free(l) i(firm) intmat(m) t(year) nbs(200)
> invest robust second
........................................................................
> .......................................................................
> ..................................................
Ackerberg-Caves-Frazer Method to Estimate Production Functions
(Non-linear heteroskedastic GMM estimates for value added)
                                                         Number of obs = 5027

             |               robust
           y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .0958997   .0191596     5.01   0.000     .0583476    .1334518
           a |   .0826269   .0198569     4.16   0.000     .0437082    .1215457
           m |   .7756028   .0508862    15.24   0.000     .6758677    .8753379
           l |   .1223262   .0608105     2.01   0.044     .0031399    .2415126

Wald test of constant returns to scale: Chi2 =  29.14 (p = 0.0000)
Sargan-Hansen J-statistic:   0.000 (p = .)
H0: overidentifying restrictions are valid
```

Our final set of results is meant to illustrate the Sargan–Hansen test and the `predict` postestimation command in a specification that is analogous to the one presented above but uses value added as the dependent variable (with investment as a proxy and standard errors robust to arbitrary heteroskedasticity). To this end, we use the `overid` option and save the estimated (log) productivity in a new variable called `omega_hat`.

```
. acfest va, state(k a) proxy(i) free(l) i(firm) t(year) nbs(200) va overid
> invest robust
.........................................................................
> .......................................................................
> ...................................................
Ackerberg-Caves-Frazer Method to Estimate Production Functions
(Non-linear heteroskedastic GMM estimates for value added)
                                                    Number of obs = 5027

             |               robust
          va |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
           k |   .1725643   .0201417     8.57   0.000     .1330873    .2120412
           a |   .2679969   .9289787     0.29   0.773    -1.552768    2.088762
           l |   .4300994   .0966996     4.45   0.000     .2405717    .6196271
------------------------------------------------------------------------------
Wald test of constant returns to scale: Chi2 =   0.02 (p = 0.8848)
Sargan-Hansen J-statistic:   1.454 (p = 0.6928)
H0: overidentifying restrictions are valid
```

The Sargan–Hansen test does not reject the validity of the moment conditions used to construct the model. Also, the Wald test supports the existence of constant returns to scale. Lastly, as observed in the revenue case, using investment rather than materials as a proxy has a major impact on the coefficients.

```
. predict omega_hat, omega
. histogram omega_hat, by(e)
```

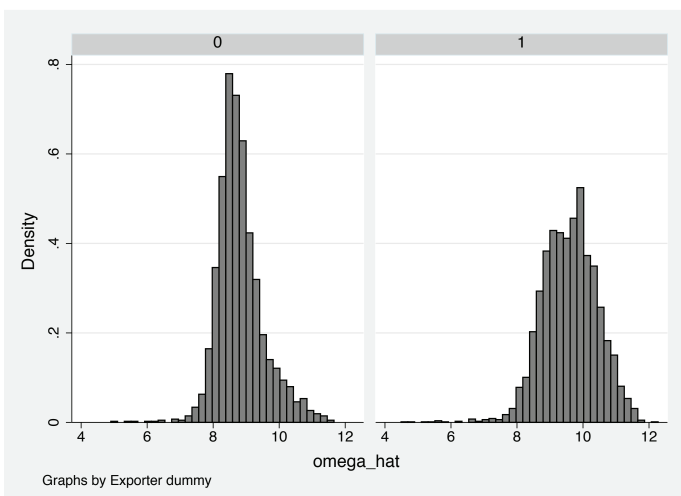

Figure 1. Exports and productivity

Figure 1, the histogram for estimated productivity, distinguishes between exporters (that is, firms that declare positive values in the exporting variable, `e`, for a particular year) and nonexporters (that is, firms that declare zero value in the exporting variable for a particular year). It turns out that the distribution of the exporters is slightly to the right of the nonexporters, which indicates that, consistent with previous findings on the exporting-productivity relation, exporting firms are more productive than nonexporting firms. Still, one should bear in mind that although this finding suggests a positive correlation between exports and productivity, it is based on a simple descriptive analysis and should not be interpreted as evidence of causality between these variables.

5 Concluding remarks

In this article, we introduced the `acfest` command, which implements a method for estimating production functions proposed by Ackerberg, Caves, and Frazer (2015). This method deals with the functional dependence problems that may arise in the approaches proposed by Olley and Pakes (1996) (implemented in Stata by Yasar, Raciborski, and Poi [2008]) and, particularly, by Levinsohn and Petrin (2003) (implemented in Stata by Petrin, Poi, and Levinsohn [2004]). The output from `acfest` also includes a Wald test (constant returns to scale) and the Sargan–Hansen J test (overidentifying conditions). Lastly, the `predict` postestimation command provides an estimate of the (log of) the productivity.

We illustrated the capabilities of the new command using data on Spanish manufacturing firms. In particular, we reported results for both revenue and value added. Estimates were as expected, meaning that, when we compared them with OLS estimates, we obtained a smaller elasticity of labor and materials and a larger elasticity of capital (see, for example, Griliches and Mairesse [1998]). We also showed that using investment as a proxy and a second- or third-order polynomial to construct the control function makes a notable difference in the estimated coefficients of materials and labor. Further, Wald tests reject the null hypothesis of constant returns to scale in the revenue specifications but not in the value-added specifications. Lastly, the Sargan–Hansen test indicates the convenience of using overidentifying conditions in the value-added specification.

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