On using proxy variables to control for time-varying unobservables while accounting for time-constant firm heterogeneity

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Abstract

Inspired by recent developments in the firm-level production function estimation literature, we suggest addressing the problem of endogeneity of labour inputs using the most recent developments of the proxy-variable approach by Ackerberg, Caves & Frazer (2006). However - unlike ACF and their predecessors - we propose doing this in combination with first differences (FD) to properly account for time-constant unobserved heterogeneity (firm fixed effects). This increases the chance of verifying the key monotonicity assumption required by the ACF approach to invert out the unobserved short-term productivity term, and completely remove the simultaneity bias. Using Belgian data we show that ACF alone delivers estimates that barely differ from OLS ones, whereas FD-ACF generates results that are similar to those delivered when, after differencing, lagged inputs are used as instruments for changes in the inputs.

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Keywords: production function estimation, proxy-variable approach, instrumental variables, heterogeneity and simultaneity bias

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1. Introduction

Production functions are a key component of many works in economics. As such, their estimation has a long history in applied economics, starting in the early 1800's. More recently, labour economists have started examining the relationship between not just labour, but various characteristics of the labour force and firms' productivity. To that end they use firm-level micro data to estimation production functions expanded by the specification of a labour-quality index à la Hellerstein & Neumark (1995) (HN henceforth).[1] The HN methodology is suitable to analyse a large scope of worker characteristics, such as race and marital status or gender. In this paper, we will consider age, but this is for a purely illustrative purpose.

Perhaps the major econometric issue confronting estimation of production functions is the possibility that some of the inputs are not observed by the econometrician. If this is the case, and if the observed inputs (e.g. the overall size of the workforce and its age composition) are chosen as a function of unobservables (as will typically be the case for a cost-minimizing firm), then there is an endogeneity problem, and OLS estimates will be biased.

Authors following the HN framework, with an interest in labour productivity, have dealt essentially with two aspects of endogeneity: *i)* heterogeneity bias (unobserved time-invariant determinants of firms' productivity that may be correlated to the workforce structure[2]) and *ii)* simultaneity bias (endogeneity in input choice, in the short-run, that includes the workforce mix of the firm[3]).

Many authors e.g. Blundell & Bond (1998) - following the dynamic panel data literature - pursue an identification strategy based on "internal" instruments (i.e lagged values of endogenous labour inputs). But the past fifteen years has seen the introduction of a couple of new techniques.. They where pioneered by Olley & Pakes (1996) (OP hereafter) and Levinsohn & Petrin (2003) (LP hereafter), and are somewhat more structural in nature. They consist of using observed input decisions (LP suggest using intermediate goods) to proxy unobserved productivity shocks causing

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[1] The key idea of HN is to estimate a production function (or a labour-cost function), with heterogeneous labour input, where different types (e.g. men/women, young/old) diverge in terms of marginal product.

[2] For instance, the age of the plant/establishment may affect productivity and simultaneously be correlated with the age of the workers; older workers being overrepresented in older ones.

[3] For instance, the simultaneity of a negative productivity shock (due to the loss of a major contract) and workforce ageing /rejuvenation stemming from either recruitment freeze or early retirement, causing reverse causality: from productivity to age structure. A recruitment freeze affects youth predominantly, and translates into rising share of older workers during negative spells, creating a negative correlation between older workers' share and productivity, thereby leading to underestimated estimates of their productivity. By contrast, if firms primarily promote early retirements (Dorn & Sousa-Poza, 2010) when confronted with adverse demand shocks, we would expect the correlation to be positive, leading to an overestimation of older workers' productivity with FD alone

the simultaneity bias.

This paper primarily considers the proxy-variable techniques, but propose implementing them in a way that eliminates one of their weaknesses: the fact that they do not allow for time-constant unobserved heterogeneity across firms (i.e firm fixed effects). A natural starting point is to consider the most recent developments of OP-LP two-step approach put forth by Ackerberg, Caves & Frazer (2006) (ACF hereafter). However - unlike ACF and their predecessors – we recommend doing this in combination with first differences (FD) to properly account for firm fixed effects.

In a sense, we stick to what is done by authors doing IV. Among authors with an interest in the age-productivity nexus, Aubert and Crépon (2003), Cataldi, Kampelmann & Ryck (2011) or van Ours & Stoeldraijer (2011) control for the heterogeneity bias using FD transformations, and deal with the simultaneity bias using lagged values of the (first-differenced) age structures as instruments for the change in the age structure.

What is more, we argue that explicitly accounting for firm fixed effects increases the chance of verifying the key monotonicity assumption required by the ACF approach to invert out the unobserved short-term productivity term, and completely remove endogeneity (more on this in Section 2). Using Belgian firm-level micro data to estimate production functions expanded by the specification of a labour-quality index à HN, we illustrate the importance of explicitly accounting for firm fixed-effects when pursuing the ACF strategy. We show that ACF alone delivers estimates that barely differ from OLS ones. Whereas FD-ACF generate results that are similar to those of IV methods connected to the dynamic-panel literature.

The rest of the paper is organized as follows. In Section 2, our methodological choices are unfolded. We expose the HN framework and our strategy to combine FD and ACF. Section 3 contains an empirical illustration.

2. Methodology

In order to estimate age-productivity profiles, following most authors in this area (Hellerstein *et al.*, 1999; Aubert & Crépon, 2003; Dostie, 2011; van Ours & Stoeldraijer, 2011), we consider the econometric version of a (linearized) Cobb-Douglas production function where labour productivity (per worker) varies is a function of the (log of) the labour quality index lq_{it} à-la-HN, the (log of) capital and a set of controls F_{it}.

$$ln\,(Y_{it}\,/L_{it}) = B + \varphi\; lq_{it} + ß\; k_{it} + \gamma F_{it} + \varepsilon_{it} \qquad (1)$$

If we considering three age groups (1=[20-29], 2=[30-49]; 3=[50-64[), with prime-age (30-49) workers forming the reference group, it can be shown[4] that the labour quality index can be approximated by:

$$\varphi\, lq_{it} \equiv (\alpha\text{-}1) l_{it} + \eta_1 P_{it}^{18\text{-}29} + \eta_3 P_{it}^{50\text{-}64} \tag{2}$$

where l_{it} is the log of the overall workforce and $P_{it}^{18\text{-}29} \equiv L_{it}^{18\text{-}29}/L_{it}$ the proportion/share of workers aged 18-29 over the total number of workers in firm i , and $P_{it}^{50\text{-}64}$ that of workers aged 50-64.

As to a proper identification of the causal links, the main challenge consists of dealing with the various constituents of the **residual** ε_{it} of equation (1). We assume that the latter comprises three elements:

$$\varepsilon_{it} = \omega_{it} + \theta_i + \sigma_{it} \tag{3}$$

where: $cov(\theta_i, P_{ik,t}) \neq 0$, $cov(\omega_{it}, P_{ik,t}) \neq 0$, $E(\sigma_{it})=0$

In other words, the OLS sample-error term potentially consists of *i)* an unobservable firm fixed effect θ_i; *ii)* a short-term productivity shock ω_{it} (whose evolution may correspond to a first-order Markov chain), and is observed by the firm (but not by the econometrician) and (partially) anticipated by the firm, and, *iii)* a purely random shock σ_{it}.

Parameter θ_i in (3) represents time-invariant firm-specific characteristics that are unobservable but driving average productivity. For example, the vintage of capital in use, the stage of the firm's product lifecycle, firm-specific managerial skills, location-driven comparative advantages.... And these might be correlated with the age structure of the firm's workforce, causing heterogeneity bias. This said, the greatest econometric challenge is to go around the simultaneity bias (Griliches & Mairesse, 1995).

To account for the presence of this simultanetiy bias, one possibility is to estimate the relevant parameters of equation (1) using only "internal" instruments and Generalized Methods of Moments (GMM). The essence of this strategy is to use lagged values of endogenous labour inputs as instruments for the endogenous (first-differenced) labour inputs (FD-IV-GMM). Aubert & Crépon, (2003); van Ours & Stoeldraijer (2011), Cataldi, Kampelmann & Rycx (2011) are recent examples of this approach. We will implement FD-IV-GMM in Section 3 to cope with simultaneity of the

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4 Vandenberghe (2011), Dostie (2011).

labour inputs (i.e. both the overall level of labour and the share by age).

But our prime interest in this paper is to explore proxy-variable methods initiated by OP-LP, and improved recently by ACF. The ACF error term writes:

$$\varepsilon_{it} = \boldsymbol{\rho_{it}} + \sigma_{it} \tag{5}$$

The latter does not explicitly contain a fixed effect θ_i, as we have assumed in (3), and as is traditionally assumed by the authors using FD-IV-GMM. In the ACF framework (similar in that respect to the LP or OP ones), the firm fixed effects are *de facto* part of $\boldsymbol{\rho_{it}}$. In other words $\rho_{it}=\omega_{it}+\theta_i$.

Like ACF, we assume that firms' (observable) demand for intermediate inputs (int_{it}) is a function of the time-varying unobserved term $\boldsymbol{\rho_{it}}$ as well as (log of) capital, and the quality of labour index lq_{it} and its components:

$$int_{it} = f_t(\boldsymbol{\rho_{it}}, k_{it}, lq_{it}) \tag{5}$$

ACF further assume that this function f_t is monotonic in $\boldsymbol{\rho_{it}}$ and its other determinants, meaning that it can be inverted to deliver an expression of $\boldsymbol{\rho_{it}}$ as a function of int_{it} , k_{it}, lq_{it}, and introduced into the production function:

$$ln\,(Y_{it}/L_{it}) = B + \varphi\, lq_{it} + ß\, k_{it} + \gamma F_{it} + f_t^{-1}(int_{it}, k_{it}, lq_{it}) + \sigma_{it} \tag{6}$$

We recommend using strategy to properly identify the labour input coefficients φ. However - unlike ACF – we advise doing this in combination with first differences (FD) to properly account for firm fixed effects θ_i, This implies assuming that firms' (observable) demand for intermediate inputs (int_{it}) is a function h only of ω_{it} and the other inputs

$$int_{it} = h_t(\omega_{it}, k_{it}, lq_{it}) \tag{7}$$

And that the production function rather writes

$$ln\,(Y_{it}/L_{it}) = B + \varphi\, lq_{it} + ß\, k_{it} + \gamma F_{it} + h_t^{-1}(int_{it}, k_{it}, lq_{it}) + \boldsymbol{\theta_i} + \sigma_{it} \tag{8}$$

We believe that explicitly accounting for firm fixed effects increases the chance of verifying the key monotonicity assumption required by the ACF approach in order be able to invert out ω_{it}, and completely remove the endogeneity problem. In the ACF framework (similar in that respect to the LP or OP ones), the firm fixed effects are *de facto* part of ω_{it}. Allowing for a time-varying firm effect is *a priori* appealing. For instance, it preserves more identifying variation.[5] On the other hand, the evidence with firm panel data is that fixed effects $\boldsymbol{\theta_i}$ capture a large proportion (>50%) of the total productivity variation.[6] This tentatively means that, in the ACF intermediate goods function $int_{it}= f_t(\rho_{it}=\omega_{it}+\theta_i, k_{it}, lq_{it})$, the term ρ_{it} can vary a lot when switching from one firm to another and, most importantly, in a way that is not related to the consumption of intermediate goods. In other words, firms with similar values of int_{it} (and ω_{it}., k_{it} or lq_{it}) could be characterized by very different values of ρ_{it}. This is something that invalidates the ACF assumption of a one-to-one (monotonic) relationship, and the claim that the inclusion of intermediate goods in the regression adequately controls for endogeneity/simultaneity. This said, we still believe that intermediate goods can greatly contribute to identification, but conditional on properly accounting for firm fixed effects. In practice, how can this be achieved? The ACF algorithm consists of two stages. We argue that only stage one needs to be adapted.

In stage one, like ACF, we regress average productivity on a composite term Φ_t that comprises a constant, a 3^{rd} order polynomial expansion in int_{it}, k_{it}, lq_{it}., and our vector of controls added linearly. This leads to

$$ln\,(Y_{it}/L_{it})= \Phi_t(int_{it}, k_{it}, lq_{it}, F_{it}) + \boldsymbol{\theta_i} + \sigma_{it} \qquad (9)$$

Note that Φ_t encompasses $\omega_{it} =h_t^{-1}(.)$ displayed in (7) and that φ, $ß$ and γ are clearly not identified yet.[7] The point made by ACF is that this first-stage regression delivers an unbiased estimate of the composite term Φ_{it}^{hat}; i.e productivity net of the purely random term σ_{it}. We argue that this is valid only if there is no firm fixed effect θ_i or if the latter can be subsumed into $\omega_{it} =h_t^{-1}(.)$ - something we believe unrealistic and problematic for the reasons exposed above. Hence, we prefer assuming that fixed effects exist and explicitly accounting for them; which can easily be done by resorting to first differencing (FD) to estimate equation (9). The FD-estimated coefficients - provided they are applied to variables in levels - will deliver an unbiased prediction of Φ_{it}^{hat}. Specifically, Φ_{it}^{hat}, net of the noise term and firm-fixed effects, is calculated as $\Phi_{it}^{hat} =(\upsilon_{a1})^{FD}\, int_{it} + (\upsilon_{a2})^{FD}\, int^2_{it} +\ldots+ (\upsilon_{b1})^{FD} k_{it} + \ldots+(\upsilon_{c1})^{FD} lq_{it}+ \ldots +(\upsilon_{d1})^{FD}\, int_{it}k_{it} \ldots$, where $(\upsilon_{a1})^{FD}$, $(\upsilon_{a2})^{FD}\ldots$ represent the first-differenced coefficient estimates on the polynomial terms.

5 Fixed-effect estimators only exploit the within part of the total variation.

6 Another illustration of the same idea is that published studies have documented, virtually without exception, enormous and persistent measured (but unexplained) productivity differences across firms, even within narrowly defined industries (Syverson, 2011).

7 Note in particular that the non identification of vector φ (i.e. labour input coefficients) in the first stage is one of the main differences between ACF and LP.

Next, we basically argue that their second stage is unaffected by the modifications discussed above. Key is the idea that one can generate implied values for $\boldsymbol{\omega}_{it}$ using first-stage estimates Φ_{it}^{hat} and candidate[8] values for the coefficients φ , $ß$, γ:

$$\omega_{it} = \Phi_{it}^{hat} - lq_{it}\,\varphi - ß\, k_{it} - \gamma F_{it} \quad (10)$$

ACF assume further that the evolution of ω_{it} follows a first-order Markov process

$$\omega_{it} = E[\omega_{it} | \omega_{it-1}] - \xi_{it} \quad (11)$$

That assumption simply amounts to saying that the realization of ω_{it} depends on some function $g(.)$ (known by the firm) of $t-1$ realisation and an (unknown) innovation term ξ_{it}.

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \quad (12)$$

By regressing non-parametrically (implied) ω_{it} on (implied) ω_{it-1}, ω_{it-2}, one gets residuals that correspond to the (implied) ξ_{it} that can form a sample analogue to the orthogonality (or moment) conditions identifying φ,$ß$ and γ. We would argue that residuals ξ_{it} are orthogonal to our controls F_{it}

$$\mathrm{E}[\xi_{it} | F_{it}] = 0 \quad (13)$$

Analogous to ACF, we would also argue that capital in period t was determined at period $t-1$ (or earlier). The economics behind this is that it may take a full period for new capital to be ordered and put to use. Since k_{it} is actually decided upon $t-1$, $t-2$…, it must be uncorrelated with the implied innovation terms ξ_{it}:

$$\mathrm{E}[\xi_{it} | k_{it}] = 0 \quad (14)$$

Labour inputs observed in t are probably also chosen sometime before, although after capital – say in $t-b$, with $0<b<1$. As a consequence, lq_{it} will be correlated with at least part of the productivity innovation ξ_{it}. On the other hand, assuming *lagged* labour inputs were chosen at time $t-b-1$ (or earlier), lq_{it-1}, lq_{it-2}… should be uncorrelated with the innovation terms ξ_{it}. This gives us the third (vector) of moment conditions needed for identification of φ:

$$\mathrm{E}[\xi_{it} | \; lq_{it-1}, lq_{it-2} \ldots] = 0 \quad (15)$$

or more explicitly, given the composite nature of lq_{it}, we have:

$$\mathrm{E}[\xi_{it} | \; l_{it-1}, l_{it-2} \ldots] = 0 \quad (15a)$$

[8] OLS estimates for example.

$$E[\xi_{it} | P^{18\text{-}29}_{it-1}, P^{18\text{-}29}_{it-2} \cdots]=0 \quad (15b)$$

$$E[\xi_{it} | P^{50\text{-}54}_{it-1}, P^{50\text{-}64}_{it-2} \cdots]=0 \quad (15c)$$

3. Empirical illustration

The aim of this section is to illustrate, using Belgian firm-level data[9], the importance of explicitly accounting for firm fixed-effects when pursuing the ACF strategy. Table 1 presents the parameter estimates of the average productivity (ie; value added per worker) (see equ. 1, Section 2), under five alternative econometric specifications. The first set of parameter estimates comes from OLS, using total variation [1]. The next strategy [2] consists of using intermediate inputs à-la-ACF. Then comes first differences (FD), where parameters are estimated using only within-firm variation [3]. Model [4] implements the Blundell-Bond strategy relying on a system of equations combining first differences and internal lagged labour inputs as instruments (FD-IV-GMM).[10] The last model [5] combines FD and the ACF intermediate-goods proxy idea (FD-ACF), ie. the focus of this paper.[11]

OLS potentially suffers from endogeneity bias. This justifies considering ACF i.e. to use intermediates goods to proxy for a plant's unobservable productivity shocks. ACF has the advantage over the more typical FD panel data approach of allowing for time-varying plant effects and allowing for more identifying variation in the other inputs. It is not, however, a complete panacea. We have explained above that it is difficult to believe in the existence of a one-to-one relationship between a firm's consumption of intermediates goods and productivity shocks ω_{it} that would systematically comprise all the firms' unobservables. Results [2] in Table 3 somehow comfort us in our *a priori* scepticism. ACF fails to take us significantly away from OLS, as point estimates are essentially identical. A 10%-points rise in the share of young workers depresses

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9 The data consists of a panel (1998 to 2006) of around 9,000 firms with more than 20 employees, largely documented in terms of sector/industry, size, capital used, productivity and intermediate inputs (value of goods and services consumed or used up as inputs in production by enterprises, including raw materials, services and various other operating expenses).

10 To be precise, we implement the "system" variant of that IV strategy, proposed by Blundell & Bond (1998). Lagged levels, although they might be orthogonal to the short-term shock ω_{it}, tend to prove poor predictors of first differences (i.e. they are weak instruments). Blundell & Bond then proposed an improved estimator called system-GMM that uses extra moment conditions. This estimator consists of a system of two equations estimated simultaneously. One corresponds to the above-mentioned first-difference equation, where the instruments are the (lagged) labour inputs in level. The second equation consists of using regressors in level, with (lagged) first-differenced of the endogenous variables as instruments. This estimator has become the estimator of choice in many applied panel data settings. By default, our Stata xtabond2 command uses, for each time period, all available lags of the specified variables in levels dated *t-1* or earlier as instruments for the FD equation and uses the contemporaneous first-differences as instruments in the level equation.

11 As suggested in Section 2 (equ. 15, 15a-c), identification is provided by a set of moment conditions imposing orthogonality between implied innovation terms ξ_{it} and k_{it} ; ξ_{it} and lags 1 to 3 of the labour inputs.

productivity by 4.1% (2.41% with OLS). A similar increment in the share of older workers lowers productivity by 2.38% (2.89% with OLS).

OLS results suffer from potentially strong unobserved heterogeneity bias. Even the inclusion of controls in F_{it}, mostly a large set of dummies[12], is probably insufficient to account for firm-level singularities that may affect simultaneously firms' productivity and age structure. First-differencing (FD) as done in [3] is still the most powerful way out of this problem. Results from this model point at a disappearance of the handicap of younger workers and a strong reduction of the apparent handicap of older workers; an increase of 10%-points of their share in the workforce depresses productivity by 0.88%. Both results are supportive of the idea that younger and older workers are overrepresented (within NACE2 industries) in firms that are intrinsically less productive.

If FD [3] probably dominates ACF [2], FD alone is not sufficient. The simultaneity bias in labour input choice is a well-documented problem in the production function estimation literature. In short, heterogeneity and endogeneity deserved to be simultaneously treated. And this is precisely what labour economics, following the dynamic panel tradition, do when resorting to [4] by estimating FD-IV-GMM. Our main point is that approach can be paralleled by combining FD with ACF (see Section 2 for the algebra), as we do in [5]. Estimations [4] and [5] in Table 1 are *a priori* the best insofar as the parameters of interest are identified from within-firm variation to control for firm unobserved heterogeneity, and that they control for short-term endogeneity biases either via the use of ACF's intermediate input proxy, or internal instruments.

Model [4], based on FD-IV-GMM, confirms that younger workers are as productive as prime-age one. It also suggests that a 10%-rise of the share of older workers depresses productivity by 2.19% (vs. 0.88% with FD).[13]

Our key result is that those from the FD-ACF model [5] are very similar to those delivered by FD-IV-GMMG (and also completely different that those from ACF [2]). Like with FD-IV-GMM (but unlike ACF) there is no difference between young and prime-age workers as to their impact on the overall labour productivity. And a 10%-points rise in the share of older workers causes a drop of productivity of 1.7% (vs. 0.88% with FD and 2.19% with FD-IV-GMM).

It is also worth stressing that models [4] and [5] deliver estimates of older workers productivity that

[12] All our models, including OLS, use data in deviations from region (Wallonia, Flanders, Brussels) plus year interacted with NACE2 industry means.

[13] In all our S-GMM estimates, reported in Table 1, our instruments pass the standard test statistics provided by xtreg2, namely Arellano-Bond test for AR(1) in first differences, Arellano-Bond test for AR(2) in first differences, Sargan test of overid. restrictions and difference-in-Sargan tests of exogeneity of instrument subsets.

are *lower* than those obtained with FD only [2]. This is supportive of the existence of a simultaneity bias, in particular that private firms based in Belgium primarily resort to early retirements - rather than recruitment freezes - to cope with negative demand shocks.

Table 1: Parameter estimates (standard errors). Young (18-30) and older (50-64) workers productivity (η^1,η^3) - Overall, unbalanced panel sample.

	[1]-OLS	**[2]-intermediate inputs ACF[$]**	**[3]-First Differences (FD)**	**[4]- FD- IV- GMM (system GMM)**	**[5]- FD+ intermediate inputs ACF[$]**
Productivity young ($\eta 1$)	-0.241***	-0.410***	0.001	-0.021	0.083
std error	*0.013*	*0.004*	*0.016*	*0.053*	*0.070*
Productivity old ($\eta 3$)	-0.289***	-0.238***	-0.088***	-0.219***	-0.174***
std error	*0.021*	*0.010*	*0.024*	*0.063*	*0.073*
#obs	79,058	38,876	68,814	79,206	38,876
Controls	All data are deviations from region+ year interacted with NACE2 industry means				
	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + **firm fixed effects**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + **firm fixed effects[a]**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + **firm fixed effects**
Orthogonality conditions/instruments used to identify endog. labour shares			Innovation in ω_{it}⫫ lag$_{1-3}$ labour shares	All available lags of labour shares, & first-differenced labour shares	Innovation in ω_{it}⫫ lag$_{1-3}$ labour shares

a: Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work.
*p < 0.05, **p < 0.01, *** p < 0.001
[$] Ackerberg, Caves & Frazer.

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