DYNAMIC PANEL DATA ESTIMATES OF A PRODUCTION FUNCTION: AN APPLICATION TO CUBAN MANUFACTURING INDUSTRY

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ABSTRACT
Production functions have been extensively used to examine Cuban's long-term sources of economic growth. Recent availability of firm-level data have made possible to extend this practice to sectorial level of aggregation yielding some questionable results. Unexpectedly low (and sometimes) non-significant elasticities of the capital variable has been systematically documented in literature. We attribute this to the existence of "methodological problems" in the production function such as simultaneity, measurement errors, or attriction. Using dynamics panel data models in the Cuban manufacturing industry we obtained more robust capital elasticities; and evidence in favor of constant return to scale hypothesis. We also document the presence of measurement errors in data.

KEYWORDS*:* Production Functions, Cuban Manufacturing Industry, Generalized Method of Moment

MSC: 91B74

RESUMEN
Las funciones de producción han sido usadas extendidamente para examinar las fuentes de crecimiento económico de largo plazo de Cuba. La disponibilidad reciente de datos a nivel de firmas ha hecho posible extender esta práctica a nivel de agregación sectorial produciéndose resultados cuestionables. Elasticidades inesperadamente bajas para la variable capital y (algunas veces) no significativas han sido documentadas sistemáticamente en la literatura. Atribuimos este hallazgo a la existencia de problemas metodológicos en la función de producción tales como simultameidad, errores de medida o desgaste muestral. Usando modelos dinámicos de datos de panel para la industria manufacturera cubana se obtuvieron elasticidades más robustas para el capital así como evidencia a favor de la hipótesis de rendimientos constantes a escala. También documentamos la presencia de errores de medida en los datos.

PALABRAS CLAVES: Función de Producción, Industria Manufacturera Cubana, Método Generalizado de los Momentos

1. INTRODUCTION

Production functions have been used extensively in exploring long-term sources of growth in Cuba. Despite initial researches based mostly on aggregated time series, the recent availability of firm-level data have allowed extending the estimates of production function to sectoral level, for instance, agriculture, tourism and manufacturing. Those researches have systematically documented a common result, that is: very low and (sometimes) non-significant estimates for capital coefficient contrasting with greater and highly significant labor coefficient estimates. Through comparing a number of recent Cuban working papers at micro level, González (2016) showed that the capital elasticity has never been greater than 0.06; whereas labor elasticity ranged from 0.3 to 0.8 across researches.

Though these findings might be reflecting – at least partially – the fundamentals, and structural features of the Cuban economy; we argue that they can also be the result of "methodological problems" that arise in the process of estimating production functions. Factors elasticities can result biased due to simultaneity, measurement errors in data, attrition, etc.; as it is recognized since Marschak & Andrews (1944). The pattern described above (in the Cuban case) is consistent with evidence collected by literature. In this paper, we shed some lights on the influence of simultaneity on consistent estimates of parameters of production functions. The methodological framework developed by Blundell & Bond (2000) is adopted in order to tackle this issue.

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It requires the estimation of a dynamic panel data production function using the Generalized Method of Moment (GMM) and a Minimum Distance estimator.
Section II explains the way in which simultaneity affects production functions. Section III states the model and explains the identification strategy followed to estimate structural parameters of production function. The data analysis and econometric implementation of our model is described in this section as well. Section IV concludes.

2. LITERATURE REVIEW: PRODUCTION FUNCTIONS AND SIMULATNEITY BIAS

Consider the following Cobb-Douglas production function without imposing constant returns to scale[2]:

$$\boldsymbol{Y_{it} = F(A_{it}, L_{it}, K_{it}, M_{it}) = A_{it}L_{it}^{\beta_l}K_{it}^{\beta_k}M_{it}^{\beta_m} \quad i = 1, \dots, N;\ t = 1, \dots, T} \tag{1}$$

where firms are indexed by *i* and the time by *t*. Y represents physical output while L, K and M are labor, capital and intermediate material, respectively. β_j with $j \in$ (l, k, m) denotes output elasticities with respect to inputs. A_{it} is a measure of each firm´s efficiency in time period *t* (unobserved in the data) which is assumed as Hicks-neutral. It represents all unobserved determinants of output, typically measured as the residuum of the production function (Solow, 1956).
Taking logarithm in equation (1) yields:

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

where log values of each element coming from equation 1 have been denoted with lower case letters.
Equation 2 is a log-linear transformation where $\ln(A_{it}) = \beta_0 + \varepsilon_{it}$.
The parameter β_0 is nothing but the mean efficiency level across firms and over time. In addition, ε_{it} represents the time-and-producer-specific deviation from β_0 that captures: i) unobserved factors affecting firm output, ii) measurement error in output and inputs, and iii) random noise (Eberhardt & Helmers, 2010).
Equation 2 can be re-written to separate unobserved factors from measurement errors and random noise:

$$\boldsymbol{y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \upsilon_{it}^* + \epsilon_{it}} \tag{3}$$

In this formulation υ_{it}^* denotes all unobserved time-variable factors; while ϵ_{it} is usually assumed as an *i.i.d.* component representing unexpected deviations from the mean due to measurement errors, 'unexpected delays' or other external circumstances (Van Beveren , 2010). As Griliches & Mairesse (1995) pointed out υ_{it}^* is "known by the producer but not by the econometrician while is exclusively an econometrician's problem".
Finally, $\omega_{it} = \beta_0 + \upsilon_{it}^*$ denotes the TFP index, which is typically obtained as a residuum after consistently estimating the parameters of the production function:

$$\boldsymbol{\widehat{\omega}_{it} = \widehat{\beta}_0 + \widehat{\upsilon}_{it}^* = y_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_m m_{it}} \tag{4}$$

The productivity levels $\widehat{\Omega}_{it}$ can be computed as the exponential of $\widehat{\omega}_{it}$.
The term $\hat{\upsilon}_{it}^*$ can be thought as the sum of (at least) three components[3]:

$$\boldsymbol{\upsilon_{it}^* = \eta_i + \gamma_t + \upsilon_{it}} \tag{5}$$

where η_i is the firm-specific and time-invariant productivity that captures all time-invariant characteristic associated to firm *i*, such as its managerial ability, its industrial sector of operation or its historical geographic location (Eberhardt & Helmers, 2010). In other words, η_i denotes the permanent deviation of firm *i* from the average firm productivity level.
The technological progress (or macroeconomic shocks) evenly affecting the entire sample is represented by γ_t. This term can be thought as the average technological progress (productivity increase) for the whole sample over time. Finally, υ_{it} denotes "the combined effect of firm-specific deviation from its own TFP level in the base period and from the common or average technological progress in period *t*" (Eberhardt & Helmers, 2010).

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[2] The formulation used here nearly follows Van Beveren (2010) although some changes were introduced to make exposition simpler.
[3] For instance, Blundell & Bond (2000) extended this structure introducing an autoregressive term to capture the impact of past productivity shocks on current input choice.

The term υ_{it}^* has attracted the attention of empirical researchers since Marschak & Andrews paper was published in 1944. It has been considered as a significant source of endogeneity when estimating production functions (see for instance: Mundlak, 1961; Griliches & Mairesse, 1995; Mairesse & Hall, 1996; Olley & Pakes, 1996; Levinsohn & Petrin, 2000; among others).
The main econometric concern in estimating equation 3 arises from the fact that inputs in production function are not independently chosen but partially determined by unobserved time-variable characteristics of the firm contained in υ_{it}^*. Since inputs "are chosen in some optimal or behavioral fashion by the producers themselves, the usual exogeneity assumptions that is required for the consistency of Ordinary Least Square (OLS) are unlikely to hold" (Griliches & Mairesse, 1995). As the estimation of equation (3) by OLS is biased, the TFP estimate - which in turn depends on the elasticities of production function - becomes biased as well.
In order to determine the direction of the bias in variable inputs – e.g. labor – consider the following profit function[4]:

$$\pi_i = p(A_i K_i^{\beta_k} L_i^{\beta_l}) - wL_i - rK_i \tag{6}$$

where π_i denotes firm's profit; p, w, r represent output price, wage and the cost of capital, respectively. It is assumed that: i) firms operate in perfectly competitive input and output markets, ii) are equilibrium prices, iii) capital is a fixed input, iv) current firm's choices of labor only affect current (but not future) profits.
The first order condition of equation 6 with respect to yields:

$$\frac{\partial \pi_i}{\partial L_i} = p\beta_L A_i K_i^{\beta_k} L_i^{\beta_L - 1} = w \tag{7}$$

And solving for L_i:

$$L_i = \left(\frac{p\beta_L A_i}{w}\right)^{\frac{1}{1-\beta_L}} K_i^{\frac{\beta_k}{1-\beta_L}} \tag{8}$$

Taking natural-logs and replacing $\ln A_i = \beta_0 + \varepsilon_i$ yields:

$$\boldsymbol{ln}\, L_i = \frac{1}{1-\beta_L}(ln\, p + ln\, \beta_l + \beta_0 + \varepsilon_i - l\, n\, w + \beta_K K_i) \tag{9}$$

The equation 9 shows explicitly that labor demand is positively related to productivity shocks ε_i. Therefore, in general, when estimating production functions any variable input will be assumed upward biased.
The sign of the bias in the capital coefficient due to simultaneity is difficult to determine when there are several inputs in the production function (Van Beveren, 2010). However, Levinsohn & Petrin (2000) stated that in two-input production functions $\hat{\beta}_k$ will be downward biased. The proof requires assuming two conditions: i) a positive correlation between capital and labor and, ii) a positive correlation of both inputs with the productivity term υ_{it}^*. Still, this bias can be offset or widen depending on whether there are other methodological issues affecting the production function, as attrition or measurement errors, or not.
In conclusion, literature review shows unequivocally that production functions are subject to empirical problems that need to be corrected. Absence of correction, it is expected that variable inputs such as labor or intermediate materials are upward biased contrary to physical capital which is expected to be downward biased. These biases are consistent with result observed in Cuba when production functions have been estimated. In the next section we introduce a dynamic panel data model in order to obtain more robust estimates of coefficients.

3. EMPIRICAL IMPLEMENTATION: THE MODEL AND THE IDENTIFICATION STRATEGY

Following Blundell & Bond (2000), the structural model for a log-linearized Cobb-Douglas production function takes the form:

$$y_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + (\gamma_t + \eta_i + \upsilon_{it} + \zeta_{it}) \tag{10}$$

$$\upsilon_{it} = \rho \upsilon_{it-1} + e_{it} \qquad |\rho| < 1 \tag{11}$$

$$e_{it}, \zeta_{it} \sim MA(0)$$

[4] The notation used here nearly follows Soderbom (2009). Intermediate materials were omitted from the benefit function for simplicity since conclusions remain the same.

where the subscript i indexes firms and t the time. The variables y, l, k and m represent the log-values of the output, labor, capital and intermediate material, respectively. β_j with $j \in (l, k, m)$ denotes output elasticities with respect to inputs. The error term is composed by: i) γ_t, which captures the Hick-neutral technological progress, ii) η_i, that represents unobserved fixed-effect, iii) υ_{it}, is an autoregressive process of order 1, iv) ζ_{it}, are serially uncorrelated measurement errors, and v) e_{it}, represents the unexpected productivity shock.
The model allows inputs (l, k and m) to be potentially correlated with η_i, υ_{it} and ζ_{it} which is the core of 'methodological issues'. Notice that in comparison to the productivity structure viewed in section II (equation 5), this one accounts for the effect of past productivity shocks on current inputs decision. This is a more credible structure since it internalizes that producers might react with delay to changes in productivity. After all, input decisions are subject to a hiring process that can generate rigidities in the response.
The introduction of one-lagged productivity term (υ_{it-1}) allows writing equation 10 as a dynamic autoregressive distributed lag regression model. To illustrate, equation 11 is rewritten as[5]:

$$\upsilon_{it} = \rho(y_{it-1} - \beta_l l_{it-1} - \beta_k k_{it-1} - \beta_m m_{it-1} - \gamma_{t-1} - \eta_i - \zeta_{it-1}) + e_{it} \tag{12}$$

Rearranging and plugging into equation 10, the following reduce-form equation is obtained:

$$\begin{aligned} y_{it} = {} & \beta_l l_{it} - \rho\beta_l l_{it-1} + \beta_k k_{it} - \rho\beta_k k_{it-1} + \beta_m m_{it} - \rho\beta_m m_{it-1} + \rho y_{it-1} + (\gamma_t - \rho\gamma_{t-1}) \\ & +(1-\rho)\eta_i + (\zeta_{it} - \rho\zeta_{it-1}) + e_{it} \end{aligned}$$

or

$$y_{it} = \pi_1 l_{it} + \pi_2 l_{it-1} + \pi_3 k_{it} + \pi_4 k_{it-1} + \pi_5 m_{it} + \pi_6 m_{it-1} + \pi_7 y_{it-1} + \gamma_t^* + \eta_i^* + \epsilon_{it} \tag{13}$$

where $\gamma_t^* = (\gamma_t - \rho\gamma_{t-1})$, $\eta_i^* = \eta_i(1-\rho)$ and $\epsilon_{it} = e_{it} + \zeta_{it} - \rho\zeta_{it-1}$. The coefficients ($\pi_j$) on lagged regressors are nonlinear combinations of ρ and the contemporaneous coefficients ($\beta_l, \beta_k, \beta_m$). Notice in addition, that the component υ_{it} is not present anymore though e_{it} still is. The term ϵ_{it} captures both measurement errors (ζ_{it}) and the idiosyncratic (unexpected) productivity shock (e_{it}). If there are measurement errors then $\epsilon_{it} \sim MA(0)$, otherwise $\epsilon_{it} \sim MA(1)$.
The identification strategy of the structural parameters $\theta = (\beta_l, \beta_k, \beta_m, \rho)$ requires: (first) to estimate consistently unrestricted parameters π_j in equation 13 subject to the next three testable common-factor restrictions $\pi_2 = -\pi_1\pi_7$; $\pi_4 = -\pi_3\pi_7$; $\pi_6 = -\pi_5\pi_7$; and (second) to build a minimum distance function from those unrestricted parameters.
Estimation of equation 13 is done through dynamic panel data methods; see for instance Arellano (2003). To illustrate, differentiating equation 13 to remove unobserved fixed-effects (η_i^*):

$$\Delta y_{it} = \pi_1 \Delta l_{it} + \pi_2 \Delta l_{it-1} + \pi_3 \Delta k_{it} + \pi_4 \Delta k_{it-1} + \pi_5 \Delta m_{it} + \pi_6 \Delta m_{it-1} + \pi_7 \Delta y_{it-1} + \Delta\gamma_t^* + \Delta\epsilon_{it} \tag{14}$$

Depending on the different assumptions made on the structure of correlation between $\Delta\epsilon_{it}$ and x_{it} (with $x_{it} = y_{it-1}$, l_{it}, k_{it}), different moment restrictions can be defined to estimate parameters of equation 14, consistently. For example, assuming the following (standard) initial conditions[6]:

$$E[l_{i1}e_{it}] = E[k_{i1}e_{it}] = E[m_{i1}e_{it}] = E[y_{i1}e_{it}] = 0; \qquad t = 2 \dots T \tag{15}$$

$$E[l_{i1}\xi_{it}] = E[k_{i1}\xi_{it}] = E[m_{i1}\xi_{it}] = E[y_{i1}\xi_{it}] = 0; \qquad t = 2 \dots T \tag{16}$$

The resulting set of moment restrictions can be defined:

$$E[l_{it-s}\Delta\epsilon_{it}] = 0 \tag{17}$$
$$E[k_{it-s}\Delta\epsilon_{it}] = 0 \tag{18}$$
$$E[m_{it-s}\Delta\epsilon_{it}] = 0 \tag{19}$$
$$E[y_{it-s}\Delta\epsilon_{it}] = 0 \tag{20}$$

If there are not measurement errors, then $s \geq 2$ which in turn implies that $\epsilon_{it} \sim MA(0)$; otherwise $s \geq 3$. This means that measurement errors produce the loss of one lagged instrument per regressor.

5 We followed (nearly) the notation used in Blundell and Bond (2000).
6 See, for instance, Blundell and Bond (2000).

The moment restrictions (17)-(20) suggest (for instance) that absence of measurement errors l_{it-2}, k_{it-2}, m_{it-2} and y_{it-2} (and earlier values) can be used as instrument for Δl_{it}, Δk_{it}, Δm_{it} and Δy_{it-1}, respectively, in equation 14. The parameters can be estimated through the Generalized Method of Moment (GMM) which implies minimizing a quadratic form built from the moment restrictions previously defined, see e.g. Arellano & Bond (1991). This is commonly known as the first-difference GMM estimator (FD-GMM).

It provides a flexible framework to deal with endogenous, predetermined or strictly exogenous regressors (Arellano, 2003). For instance, if capital was not considered as endogenous but a predetermined variable (which is a common setup); another lag could be employed as instrument for Δk_{it}; involving the same moment restriction represented by (18) but with $s \geq 1$.
However, FD-GMM has shown "poor finite sample properties (bias and imprecision) when the lagged levels of the series are weakly correlated with subsequent first difference" (Blundell & Bond, 2000). Weak instrument can arise in this framework when the value of autoregressive parameter (ρ) increases to unity; and/or the variance of permanent effects (η_i) increases relative to the variance of the transitory shocks (ϵ_{it}). Since the time series of labor, capital, intermediate materials and output are generally considered as persistent, the weak instrument problem is likely to emerge.
In that case, Blundell and Bond (2000) shows that an additional set of moment restrictions must be used to increase efficiency of estimates. Assuming $E[\Delta l_{it}\eta_i^*] = E[\Delta k_{it}\eta_i^*] = E[\Delta m_{it}\eta_i^*] = 0$; and that the initial condition satisfies $E[\Delta y_{i2}\eta_i^*] = 0$; the following restrictions can be added to the original set:

$$\boldsymbol{E[\Delta l_{it-s}(\eta_i^* + \epsilon_{it})] = 0} \tag{21}$$

$$\boldsymbol{E[\Delta k_{it-s}(\eta_i^* + \epsilon_{it})] = 0} \tag{22}$$

$$\boldsymbol{E[\Delta k_{it-s}(\eta_i^* + \epsilon_{it})] = 0} \tag{23}$$

$$E[\Delta y_{it-s}(\eta_i^* + \epsilon_{it})] = 0 \tag{24}$$

where $s = 1$ if $\epsilon_{it} \sim MA(0)$, and $s = 2$ if $\epsilon_{it} \sim MA(1)$. This is commonly called as System-GMM estimator (Sys-GMM). Further technical details omitted here can be found in Arellano & Bover (1995), Blundell & Bond (1998), Blundell & Bond (2000), Arellano (2003), Roodman (2006), among others.
Sys-GMM led to improvements in efficiency of estimates becoming widely used in empirical studies of production functions. In addition, Van Biesebroeck (2007) found that in presence of large measurement errors and technological heterogeneity, Sys-GMM produced the most robust productivity level and growth estimates among a number of parametric estimators. However, some drawbacks still persist; for instance, it has not been completely clarified if Sys-GMM is a suitable framework to solve the weak instrument problem when the variance of firm-effects is larger than the variance of productivity shocks (Bun & Windmeijer, 2009).
Having estimated (consistently) the unrestricted parameters π_j (a vector of dimension $S \times 1$), the target is to obtain estimates of θ_j (structural parameters of dimension $P \times 1$). Blundell & Bond (2000) suggested the use of a minimum distance function to link both parameter sets. It must be recalled that π is a vector of nonlinear combinations of ρ and the contemporaneous coefficients $\beta_l, \beta_k, \beta_m$. Therefore, θ is related to π through function $h(\cdot)$ with $S > P$, in particular, $\pi = h(\theta)$.
The idea behind minimum distance estimation is to choose those values of $\hat{\theta}_j$ making the distance between $\hat{\pi}$ and $h(\hat{\theta})$ as small as possible; see e.g. Wooldridge (2002). The resulting estimator is derived from:

$$\boldsymbol{min_{\theta \in \Theta}\ \{\hat{\pi} - h(\theta)\}'\ \Omega\ \{\hat{\pi} - h(\theta)\}} \tag{25}$$

where Ω is an optimal $S{\times}S$ weighting matrix. In this case, the expression $\hat{\pi} - h(\theta)$ takes the form:

$$\hat{\pi} - h(\theta) = \psi(\theta) \begin{pmatrix} \pi_1 & -\beta_l \\ -\dfrac{\pi_2}{\pi_7} & -\beta_l \\ \pi_3 & -\beta_k \\ -\dfrac{\pi_4}{\pi_7} & -\beta_k \\ \pi_5 & -\beta_m \\ -\dfrac{\pi_6}{\pi_7} & -\beta_m \\ \pi_7 & -\rho \end{pmatrix}$$

where estimates of $\hat{\theta}$ are obtained following:

$$\boldsymbol{\hat{\theta} = \begin{pmatrix} \hat{\beta} \\ \hat{\rho} \end{pmatrix} = \arg\min_C \psi(C)' Var[\psi(C)]^{-1} \psi(C)} \tag{26}$$

Finally, $Var\ \psi(C)$ is estimated using Delta Method. Further analytical details about minimum distance function can be found, for example, in Wooldridge (2002) and Cameron & Trevedi (2005).

3.1. Data and some basic statistic analysis

Data come from the National Office of Statistics and Information of Cuba; and we will use a sample of Cuban state-owned enterprises to illustrate the previous discussion. These firms are required to submit information from their accounting books (and other sources). In particular, data employed in this research were collected through three specific accounting registers: *Modelo 5903*, *Modelo 5901* and *Modelo 5073*. Based on that information we built an unbalanced panel data sample of 607 state-owned manufacturing plants in period 2007-2011 (2469 observations). The sample represents between 63 and 74 per cent of the population of state-owned manufacturing firms in Cuba. Despite there are not gaps in enterprises time series data, the sample features some level of attrition. While 60% of firms never leaves the sample 10% is only present either one or two of the five years.

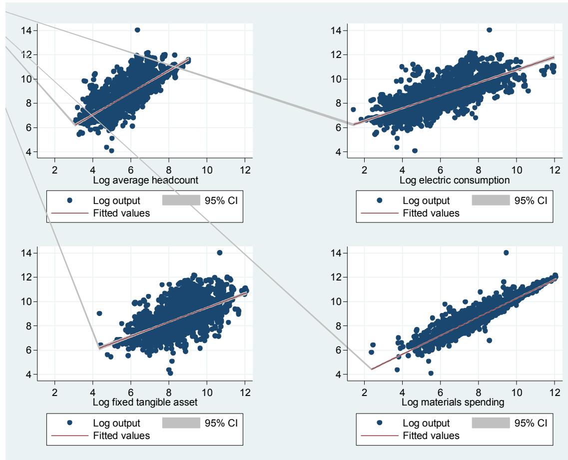
Table 1 Variables: General Information

Variable	**Indicator**	**Description**	**Source**
Output (y)	Net Sales	Gross sales minus taxes plus subsidies	*Modelo 5903**
Labor (l)	Average headcount	It is the average of total headcount at the end of the year and total headcount at the beginning of the year	*Modelo 5903**
Capital (k)	Tangible fixed assets	Long-term assets that has a physical form such as buildings, computer equipment, software, furniture, machinery and vehicles	*Modelo 5901**
Intermediate Materials (m)	Materials spending	The monetary value of raw materials, energy, and fuel	*Modelo 5903**
Electric Energy Consumption (e)	Energy consumed from electric network	It is the actual energy demand of firm that is measured in MWh	*Modelo 5073**
Labor Productivity	Productivity	Ratio of gross value added to average headcount	*Modelo 5903**
Price deflator	GDP Deflactor	-	http://www.one.cu
Price deflator	Manufacturing Deflactor (2-dig)	-	http://www.one.cu
Industry Sector	NAE code	-	*Modelo 5903**
Ministry	Ministry code	-	*Modelo 5903**

Firms are classified according to their industry of operation by *Nomenclador de Actividad Económica (NAE)*, and by ministries. The sample contains information on firms at the end of the year, e.g. sales, materials spending, fixed tangible assets, average headcount, labor productivity, etc. All variables were expressed in US$ current currency through the official exchange rate[7]. They were deflated using either the 2-digit manufacturing deflator or the GDP deflator provided by the statistic office. Table 3 displays other details about the set of indicators employed.

Graph 1 Linear Relation Output and Inputs

[7] Cuba has a dual currency system that creates a number of issues when working with economic data. In particular, it is a significant source of measurement errors.



Notes: * http://www.one.cu/sien2016.htm

The correlation between the log-value of output and the log-value of labor, capital and intermediate materials is linear (see graph 1) and strong. Their pairwise correlation coefficients are over 0.7. Electricity consumption only correlates strongly with tangible fixed asset (its pairwise correlation coefficient equals 0.82). Under certain assumptions this finding would allow using the electricity consumption as an instrument for tangible fixed assets usually measured with error.

Table 2 reports the between and within variation of the sample. In general overall data variation is not sizeable. For all variables there is more variation across individuals (between variation) than over time (within variation). Therefore, we expect to obtain imprecise estimates of coefficients in the fixed-effect model. This might be potentially explaining why estimation of static models has yielded unsatisfactory results as it was discussed in the previous section.

Table 2 Between and Within Sample Variation

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**
Output	overall	8.66	1.22	4.06	14.04	N = 2469
	between		1.23	5.20	12.28	n = 607
	within		0.26	6.65	10.41	T-bar = 4.06
Average headcount	overall	5.76	0.98	3.09	9.05	N = 2469
	between		0.98	3.12	9.01	n = 607
	within		0.16	4.29	6.90	T-bar = 4.06
Tangible F. Assets	overall	8.58	1.27	4.35	12.07	N = 2469
	between		1.24	5.13	12.03	n = 607
	within		0.26	5.86	10.63	T-bar = 4.06
Material Spending	overall	7.90	1.50	2.38	12.08	N = 2469
	between		1.49	3.42	11.89	n = 607
	within		0.32	5.72	9.98	T-bar = 4.06
Electricity Consumption	overall	6.02	1.67	1.44	11.97	N = 2469
	between		1.63	2.15	11.93	n = 607
	within		0.27	3.22	8.83	T-bar = 4.06

Notes: All variables are in log-values

In order to analyze the degree of persistency, table 3 provides $AR(1)$ estimates of all variables involved in the analysis using different estimators. OLS results suggest that both output and inputs are highly persistent with autoregressive parameters over 0.95. Within group estimator make parameters to drop dramatically to less than 0.45. Diff-GMM and within group estimators yield similar results which can be interpreted as evidence of weak-instrument presence (Blundell & Bond, 2000). The pattern of intermediate materials and (even more) electricity consumption seems to validate this hypothesis. Finally, although Sys-GMM yields results closer to OLS, a test of validity additional moment restrictions (incremental Sargan) rejects the hypothesis of compatible instruments.

Table 3 Level of Persistency in Variables

	OLS Level	Within Group	Difference Gmm	System Gmm	Difference Gmm	System Gmm
y			t − 2	t − 2	t − 3	t − 3
y_{it-1}	0.987	0.275	0.200	0.910	1.303	0.873
	(0.008)	(0.040)	(0.086)	(0.036)	(0.778)	(0.041)
m_1^*	0.255	0.000	0.024	0.000	0.113	0.000
m_2^*	0.005	0.000	0.019	0.011	0.048	0.000
$Sargan^*$	-	-	0.000	0.000	-	0.004
$D.Sargan^*$	-	-	-	0.000	-	0.051
l						
l_{it-1}	0.983	0.498	1.117	1.016	3.749	1.083
	(0.004)	(0.044)	(0.438)	(0.063)	(1.848)	(0.118)
m_1^*	0.017	0.004	0.068	0.000	0.130	0.000
m_2^*	0.815	0.000	0.418	0.424	0.317	0.369
$Sargan^*$	-	-	0.000	0.000	0.449	0.000
$D.Sargan^*$	-	-	-	0.000	-	0.000
k						
k_{it-1}	0.959	0.131	0.907	0.414	0.899	0.825
	(0.007)	(0.068)	(0.180)	(0.116)	(0.244)	(0.102)
m_1^*	0.001	0.000	0.004	0.002	0.019	0.004
m_2^*	0.389	0.000	0.295	0.121	0.322	0.283
$Sargan^*$	-	-	0.682	0.044	0.332	0.334
$D.Sargan^*$	-	-	-	0.005	-	0.305
m						
m_{it-1}	0.988	0.246	0.195	0.797	1.768	0.910
	(0.006)	(0.039)	(0.071)	(0.048)	(1.083)	(0.045)
m_1^*	0.007	0.000	0.005	0.000	0.116	0.000
m_2^*	0.054	0.000	0.120	0.113	0.485	0.149
$Sargan^*$	-	-	-	0.000	0.027	0.001
$D.Sargan^*$	-	-	-	0.000	-	0.002
e						
e_{it-1}	0.990	0.379	-0.113	0.982	-0.382	0.910
	(0.004)	(0.044)	(0.209)	(0.034)	(.248)	(0.042)
m_1^*	0.574	0.000	0.647	0.000	0.210	0.000
m_2^*	0.010	0.000	0.019	0.000	0.066	0.000
$Sargan^*$	-	-	-	0.000	0.000	0.000
$D.Sargan^*$	-	-	-	0.582	-	0.000

Notes: Clustered standard errors in parenthesis for OLS and WG estimates.* implies that p-values are reported.

3.2. Further statistical analysis: static model estimates

As we commented in the introduction section, previous estimates of production functions in Cuba have produced questionable result. In general, very low elasticity of capital and strongly significant elasticity of labor and raw materials. In this section, we investigate whether these issues arise or not in data used in the

Output	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	RE	FE	FD	OLS	RE	FE	FD	FE (IV)
k	-	-	-	-	-0.023**	0.011	0.029	0.039**	0.504**
	-	-	-	-	(0.009)	(0.013)	(0.018)	(0.017)	(0.197)
m	0.636***	0.585***	0.521***	0.487***	0.641***	0.592***	0.531***	0.498***	0.528***
	(0.010)	(0.019)	(0.028)	(0.033)	(0.010)	(0.019)	(0.028)	(0.033)	(0.016)
l	0.315***	0.353***	0.411***	0.375***	0.333***	0.361***	0.418***	0.374***	0.109
	(0.011)	(0.021)	(0.048)	(0.069)	(0.011)	(0.021)	(0.049)	(0.071)	(0.131)
e	-0.002	0.022**	0.048***	0.061***	-	-	-	-	-

current work. We start using some basic estimators in order to briefly illustrate and comment the main features of these data.

Model estimates in table 4 correspond to a production function represented by equation 3 under different assumption on υ_{it}^{*}. For instance, in the OLS estimates, υ_{it}^{*} is absorbed by ϵ_{it} and assumed to be uncorrelated with inputs; whereas in FE estimates υ_{it}^{*} is assumed to be constant through time and uncorrelated with past, present and future inputs realizations (strict exogeneity assumption). In reality they correspond to standard static panel data assumptions that are required to identify consistently the set of parameters involved, see e.g. Wooldridge (2002).

Table 4 Static Production Function Estimates

	(0.007)	(0.011)	(0.018)	(0.021)	-	-	-	-	-
Cte	1.763***	1.805***	1.851***	-0.011	1.791***	1.752***	1.788***	0.007	-0.456
	(0.073)	(0.134)	(0.256)	(0.024)	(0.068)	(0.127)	(0.269)	(0.024)	(0.945)
Time D.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry D.	Yes	Yes	-	Yes	Yes	Yes	-	Yes	-
Ministry D.	Yes	Yes	-	Yes	Yes	Yes	-	Yes	-
Obs.	2469	2469	2469	1862	2469	2469	2469	1862	2469
R-squared	0.939	0.937	0.907	0.526	0.939	0.937	0.907	0.524	.
# of Cod.	607	607	607	607	607	607	607	607	607
Hausman T.	-	-	0.000	-	-	-	0.000	-	-
CRS test	0.000	0.012	0.640	0.199	0.000	0.016	0.590	0.142	0.057

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Hausman test uses FE and RE estimates where the p-values are reported. CRS is the Wald test of constant returns to scale (p-values reported).

Two measures of capital were considered, that is, tangible fixed assets and energy consumed from electric network. The latest is usually assumed as a proxy of capital use, particularly, when depreciation is not available. We consider four models in columns 1-8 in table 4: OLS, Random Effects, Fixed Effects and First Differences. Taking into consideration that the stock of capital in large firms is usually measured with error, we use electricity consumption as an instrument for tangible fixed assets (recall from previous section that its correlation coefficient equals 0.82). Column 9 report the estimate of Fixed-effect Instrumental Variable model.

OLS estimates (columns 1 and 5) suggest that either tangible fixed assets or electricity consumption produce similar results. A negative (and significant) elasticity for capital arises when tangible fixed assets are used. In addition, the hypothesis of constant return to scale (CRS) is rejected in both cases at every level of significance. These results coincide with evidences found in international or domestic studies.

The random effect model produces a positive and significant elasticity for capital coefficient when electricity consumption is employed (column 2), while a non-significant elasticity when tangible fixed assets are considered (column 6). More of the same happens when the Fixed-Effect model is estimated, though elasticity of capital doubles compared to random effect estimate. A possible explanation for this might be the fact that variation of electricity consumption is greater than variation of tangible fixed assets. A Hausman test confirms that individual-specific effects play a role which validates the use of the FE model rather than the Random Effect model. Furthermore, CRS hypothesis was clearly not rejected under this specification.

Although fixed-effect model seems to work well here, there is still a drawback. Columns 4 and 8 report estimates of First Difference model which differ "substantially" from FE estimates. Wooldridge 2002 suggests that when this difference cannot be attributed to random differences, one should suspect that the strict exogeneity assumption is failing to hold. Since consistency of parameter depend critically on this assumption, its violation would produce unreliable estimated coefficients. The violation can be due to either measurement errors in regressors or the existence of feedbacks from past productivity shocks to current inputs decisions (Soderbom, 2009).

In order ro correct under the presence of measurement errors, ew introduce an IV estimation. Colum 9 provides an estimate of a Fixed-Effect Instrumental Variable model where tangible fixed assets were instrumented using the electricity consumption. The capital coefficient rose noticeably from 0.039 to 0.504 while the labor coefficient dropped to its lowest value. We will take this number as an upper-bounded measure since there is not any previous IV estimate in Cuban literature to compare it. In the next section we will move towards estimating the dynamic production function to appraise whether the questions raised here can be adequately answered.

3.3. Dynamic production function estimate

Table 5 reports estimates of the restricted and unrestricted models (equations 10 and 13, respectively). The following four estimators will be considered as in Blundell & Bond (2000): OLS, WG, FD-GMM and Sys-GMM; without imposing constant return to scale.

Table 5 Dynamic Production Function Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output	OLS Levels	Within Groups	DIF GMM	DIF GMM	SYS GMM	SYS GMM	SYS GMM	SYS GMM
	-	-	*t-2*	*t-3*	*t-2*	*t-3*	*t-3 + elect.*	*Mixed*
l	0.397***	0.403***	-0.209	0.672	0.164	0.607*	0.472*	0.811*
	(0.033)	(0.035)	(0.232)	(0.595)	(0.149)	(0.338)	(0.254)	(0.445)
l_{it-1}	-0.299***	0.050	0.313	0.362	0.077	- 0.258	- 0.215	- 0.392
	(0.033)	(0.035)	(0.234)	(0.497)	(0.136)	(0.300)	(0.242)	(0.388)
k	0.026*	0.007	0.018	- 0.264	0.108	0.190	0.137	0.289*
	(0.014)	(0.016)	(0.148)	(0.297)	(0.079)	(0.176)	(0.137)	(0.173)
k_{it-1}	- 0.039***	- 0.038**	-0.236***	- 0.279	-0.128***	- 0.061	- 0.089	- 0.063
	(0.014)	(0.017)	(0.077)	(0.181)	(0.041)	(0.143)	(0.115)	(0.095)
m	0.520***	0.500***	0.407***	0.286	0.567***	0.492***	0.482***	0.460**
	(0.013)	(0.015)	(0.143)	(0.257)	(0.075)	(0.157)	(0.128)	(0.185)
m_{it-1}	-0.310***	0.038*	0.052	0.243	-0.148***	-0.151	-0.208	-0.111
	(0.016)	(0.020)	(0.106)	(0.536)	(0.053)	(0.181)	(0.140)	(0.232)
y_{it-1}	0.695***	0.000	0.292***	-0.034	0.393***	0.297	0.413***	0.236
	(0.016)	(0.026)	(0.082)	(0.352)	(0.052)	(0.209)	(0.141)	(0.274)
m_1	0.002	0.000	0.010	0.448	0.000	0.018	0.000	0.031
m_2	0.212	0.000	0.012	0.088	0.838	0.321	0.265	0.318
Sargan	-	-	0.347	0.930	0.000	0.551	0.155	0.984
D.Sargan	-	-	-	-	0.000	0.596	0.261	0.962
Time D.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. D.	Yes	Yes	-	-	Yes	Yes	Yes	Yes
Min. D.	Yes	Yes		-	Yes	Yes	Yes	Yes
R^2	0.97	0.98	-	-	-	-	-	-
β_l	0.363***	0.403***	- 0.137	0.659	0.403***	0.512***	0.437***	0.648***
	(0.023)	(0.031)	(0.228)	(0.537)	(0.076)	(0.097)	(0.043)	(0.196)
β_k	0.030**	0.007	0.143	- 0.264	0.127*	0.192	0.105	0.302*
	(0.013)	(0.016)	(0.122)	(0.245)	(0.077)	(0.144)	(0.108)	(0.162)
β_m	0.559***	0.500***	0.421***	0.298	0.605***	0.474***	0.455***	0.441***
	(0.012)	(0.015)	(0.123)	(0.214)	(0.056)	(0.100)	(0.093)	(0.107)
ρ	0.744***	0.000***	0.422***	- 0.067	0.426***	0.338**	0.440***	0.310***
	(0.014)	(0.000)	(0.064)	(0.019)	(0.048)	(0.154)	(0.115)	(0.115)
Comfac	0.000	1.000	0.084	0.998	0.009	0.991	0.961	0.979
CRS test	0.061	0.004	0.018	0.640	0.354	0.479	0.752	0.299
Obs.	1862	1862	1294	1294	1862	1862	1862	1862

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Comfac* is a minimum distance test of the non-linear common factor restrictions imposed in the restricted models (p-values reported). CRS is the Wald test of constant returns to scale (p-values reported). GMM results are based on one-step GMM estimator.

Column (1) and (2) report the OLS and within group estimates of the parameters, respectively. The pattern of the signs is the expected from AR (1) error component specification in the reduced form equation estimated by OLS. The coefficient on the lagged dependent variable was significantly lower in the FE specification than in the OLS one. This might be induced by the Nickell-bias that is grounded on the contemporaneous correlation between regressors and residuals resulting from the within transformation (Arellano, 2003).
The hypothesis of non- autocorrelation of order 2 was satisfied in the OLS estimate; while both the common factor restriction and the CRS hypothesis were rejected. The capital coefficient estimated by WG was not statistically different from zero which contrasts with a low but significant OLS capital coefficient.
Estimates using one-step FD-GMM are reported in columns (3) and (4) for lagged instruments dated $t-2$ and $t-3$, respectively. We did not find any significant coefficient when instruments dated $t-3$ (and earlier) were employed. The sign of the elasticities are not the expected from the AR(1) model in both specifications. Two factors already introduced might be explaining these results. First, the presence of weak instruments due to highly persistent time series; and (second) measurement errors in inputs. Evidences of such a kind of problems in the data were provided in previous section.
Columns (5) to (8) show Sys-GMM estimates. We used four different sets of instruments that combined lagged level regressors with lagged first-differenced ones. For instance, in column (6) lagged level instruments dated $t-3$ (and earlier) were combined with lagged first-differenced regressors dated $t-2$ (see section III). Furthermore, in column (7) we added the electricity consumption variable as an external instrument in order to account for measurement errors. The preferred estimate - column (8) - uses a different set of internal instruments. Instruments dated $t-2$ (and earlier) were used for the capital variable whereas $t-3$ (and earlier) were used for the rest of regressors.
Compared to the other estimators, Sys-GMM provides the greatest estimates of the restricted capital coefficient (yet not always statistically significant). The Sargan and the incremental Sargan tests validate the addition of lagged first-difference equation as instrument for the level equation in columns (6) to (8). This strategy was rejected when instruments dated $\mathrm{t}-2$ were employed (see column 5) which means (or proves) statistical evidence in favor of the presence of measurement errors (Blundell and Bond, 2000).
Order 2 serial correlation in residuals was not found (see m_1 and m_2 tests) suggesting that the coefficients in the unrestricted model were consistently estimated. Finally, both the common factor restriction and the CRS hypothesis were not rejected in columns (6)-(8) which support the identification strategy.
The use of the electricity consumption as an external instrument does not improve estimate of the restricted capital coefficient $\beta_k = 0.105\ (0.108)$. This was an unexpected result since, as it was shown in the previous section, the IV strategy provided the highest estimates of this parameter. Nevertheless, once the set of lagged instruments for this particular regressor was expanded from $\mathrm{t}-3$ to $\mathrm{t}-2$ (and earlier), the restricted coefficient rose considerably to 0.302 (0.162). Since this last specification passes all validation criteria, we will assume this one as the best (and preferred) estimates. Notice that this elasticity is six times greater than those ones observed in the Cuban literature of production function which suggest that either simultaneity or measurement errors (or both) are present in data at hand. The problems with previous estimates rely on the fact that static panel data estimators are not robust enough to deal with this class of issues.

4. FINAL REMARKS

The availability of Cuban data at micro-level since 2010 has made possible to extend productivity analysis in several directions. Domestic literature seems to reflect common issues tackled by econometric theory at international level in last seven decades. Through the use of an unbalance panel data sample of 607 state-owned enterprises of Cuban manufacturing industry in period 2007-2011 some statistical evidence was collected and summarized as follows:

- Production functions estimates need to be corrected by more sophisticated econometric techniques in a way that internalizes methodological issues that commonly arise in this process. Neither OLS nor FE seems to be adequate strategies to consistently estimate the parameters of production functions. They provide very low and (sometimes) no significant estimates of the capital coefficient as well as rejection of the constant return to scale hypothesis; which in turn produces unreliable TFP estimates. Using a wide range of static panel data estimators, the capital coefficient reached at most 0.039 (0.017) in the FD estimate.
- International evidence suggests that measurement errors might be substantial when estimating production functions. We approached this problem instrumenting the capital stock variable with electricity consumption in a fixed-effect IV estimate; and using the Sys-GMM estimator that has been

found to provide the most reliable estimates in presence of measurement errors (Van Biesebroeck; 2007). We found a coefficient for capital equals to 0.504 (0.197) and 0.302 (0.162) in the IV and Sys-GMM estimates, respectively.

- Blundell and Bond (2000) strategy was employed in order to robust previous results. The capital coefficient estimate changed from 0.030 in the OLS specification to 0.302 in the preferred Sys-GMM one. The additional use of lagged differences as instrument for the level equation was validated by both Sargan and incremental Sargan tests. The estimated model passed the second-order serial correlation test (m_2). Therefore, consistency of parameters was validated. High persistency in both the dependent variable and regressors might be explaining why FD-GMM performs poorly when coefficients are estimated.

The strategy followed in this paper produced a coefficient for the capital variable greater than 0.06 (a referent value in previous researches). Our estimates are more in concordance to economic theory and to general knowledge on Cuban economy. As we have mentioned already, results indicate that production functions estimates based on static panel data models will be likely biased, and thus, more advanced econometric modeling will be required. Nevertheless, as researches on these matters in Cuba are just at a very initial stage, we suggest taking these results with precaution. Rather than getting to the "true" value for the capital coefficient; this paper aimed to open a new field of research in our country. Notice that simultaneity is not the only methodological problem that affects production functions estimates, and therefore, future efforts will be required to correct for them.

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