INVESTMENTS IN ICT- CAPITAL AND PRODUCTIVITY OF SMEs EMPIRICAL EVIDENCE FROM CAMEROON

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Abstract:

Despite the large body of firm-level analyses devoted to the impact of Information and Communication Technologies (ICT)-capital on productivity, a robust empirical evidence for developing countries is still needed. Starting from a commonly employed production function framework, the aim of this paper is to provide robust estimates of the impact of ICT on Cameroonian firms' productivity using a balanced panel data set.

Our findings suggest that finite sample bias due to weak instruments is a potential problem when relying on first-differenced Generalize Method of Moment (GMM) estimator. The application of the extended GMM estimator, with more informative instruments, improves the efficiency of estimates and gives more reasonable results. Specifically, we find that ICT has a negative and significant impact on firm's productivity in Cameroon.

Keywords: GMM estimators, ICT, Productivity.

I- Introduction

Despite the large body of firm-level analyses devoted to the impact of ICT-capital on productivity, a robust evidence for developing countries is still needed. In fact, development can no longer be understood without full consideration of the real effects of ICT on enterprises performance (Arjun, 1999; UNCTAD, 2003; 2005). Thus, starting from a commonly employed production function framework, our aim is to estimate the elasticity of output with respect to ICT-capital using a balanced panel dataset of Cameroonian firms. The sample used is from the short-term trends survey conducted by the Department of Forecasting at the Ministry of Economy and Finance, Cameroon, since 2000.

The productivity gains from using ICT-capital stem from the role that ICT plays as input in the production process of the firm: By substituting ICT-capital to other inputs, especially labour, ICT provides firm with the opportunity to reduce transaction costs and improve coordination of various activities, not only inside the firm (Dedrick et al., 2002), but also outside with the various partners. By using ICT as a mean to innovate – to develop processes and organisational structures-, ICT improve the efficiency of the overall inputs use.

The role of ICT in promoting firm's productivity has attracted particular attention in Cameroon since 1995, with the launch of a nationwide program to further the diffusion of ICT. The ICT-SCAN survey, conducted by the National Institute of Statistics in 2006 to evaluate ICT diffusion in the country, reveals that nearly 56% of firms have invested in ICT-capital. However, compared to their overseas counterparts, Cameroonian firms have been less active in their ICT investments which represent, in average, less than 7% of their total investment considering the sample of the short-term trends survey between 2000 and 2006.

The prospects for appropriate ICT uptake and realisation of productivity gains seem less favourable giving the macro-environment in Cameroon, and it is perhaps why firms have invested less in ICT. In fact, lack of fast internet services could limit the use of on-line services; lack of suitable telecommunication infrastructure could hamper fast and efficient global market operations; high costs of ICT equipments could reduce their anticipated benefits for the firm. All those factors can put a brake on the uptake of ICT productivity gains by individual firms.

This paper follows an econometric approach to determine whether or not firms which invested in ICT benefited from productivity gains. The emphasis will be on the use of a robust estimator intended to reveal the real rather than the spurious productivity effects of ICT.

Several studies used Ordinary Least Squares (OLS) to estimate the production function parameters (Matambalya and Wolf, 2001; Müller-Falcke, 2002; Chowdhury and Wolf, 2006). But, as it is stressed in the econometric literature, OLS may lead to distortions in quantitative results in the presence of individual heterogeneity or endogeneity. These sources of bias in OLS results –unobserved heterogeneity and endogeneity- can be controlled for. However, they have tended to yield less satisfactory parameter estimates (Griliches and Mairesse, 1998).

The application of standard GMM estimators, which take first differences to eliminate unobserved firm-specific effects and used lagged instruments to correct for the endogeneity in first-differenced equations, has produced rather unsatisfactory results in the case of panel with small number of time periods. Specifically, the elasticities of inputs are generally low and statistically non significant. The reason is the high persistence of output and input involved in the estimation of the production function: the series on firm sales, capital and employment are highly persistent so that their lagged levels are weak instruments for the first difference of these series (Blundell and Bond, 2000).

Arellano and Bover (1995) and Blundell and Bond (2000) later on, proposed to use an extended GMM estimator in which lagged first-differences of the series are used as instruments for the equations in levels, in addition to the usual lagged levels as instruments for equations in first-differences. Empirical research works by Alonso-Borrego and Sanchez-Mangas (2001), Hempell (2002) and Heyer et al. (2004) confirmed that the extended GMM estimator, called GMM-SYS, is more efficient than the standard first difference GMM estimator.

In this paper, we apply the extended GMM estimator to obtain the elasticity of output with respect to ICT-capital for Cameroonian manufacturing firms. This will help us formulate new and targeted policy decision to enhance ICT contribution to economic growth. Further, we compare our results to those obtain from the standard GMM estimator.

The rest of paper is organised as follows: section II set out the econometric model. It is based on a simple Cobb-Douglas production function with two inputs: capital and labour with capital divided in two components: ICT-capital and conventional capital. Section III illustrates why the GMM-SYS estimator is our preferred estimator. Section IV contains a description of the dataset. Section V presents estimation results. Section VI puts forward some possible explanations. Section VII concludes.

II- Econometric model

The Cobb-Douglas production function framework for a firm i at time t is expressed as follow:

$$Y_{it} = F\left(A_{it}, L_{it}, ICT_{it}, K_{it}\right) = A_{it} * L_{it}^{\alpha_1} * ICT_{it}^{\alpha_2} * K_{it}^{\alpha_3} \qquad i=1\ldots\ldots\text{N};\ t=1\ldots\ldots\text{T}. \qquad [1]$$

Y = sales;

L = employment;

ICT= amount invested in ICT equipment;

K= amount invested in conventional capital, that is non- ICT investment;

A = residual.

Firm knows A_{it} when making an input choice, but econometrician does not observe (see Marshak and Andrews, 1944).

Standard econometric analysis considers that there are many other factors that can affect the dependent variable, but which are not explicitly included in the model as explanatory variables. These factors are then approximated by the structure of the residual.

Three types of omitted variables can be considered here: Firstly, there are factors which influence the dependent variable and which varies over time and individual considered. Secondly, there also exist factors which affect in an identical way all the individuals, but whose influence depends on the period considered (time-specific effect). Thirdly, other factors can reflect structural differences which do not change over time. Every individual has a fixed value of this latent component (individual-specific effect).

Therefore, the residual A_{it} of the equation [1] can be decomposed in three components as follow (see Hsiao, 1986) with $i \in [1, N]$ and $t \in [1, T]$:

$$A_{it} = \eta_i + \gamma_t + \varepsilon_{it} \qquad [2]$$

The variables η_i are time-invariant firm-specific effects, which allow for unobserved heterogeneity in the mean of the sales series across individuals. The variables γ_t are time-specific effects, strictly identical across individuals. ε_{it} is the component of the residual term which is orthogonal to η_i and γ_t. A key assumption we maintain throughout is that ε_{it} is a disturbance term independently and identically distributed, which satisfy the following assumptions:

- $E(\varepsilon_{it}) = 0$
- $E(\varepsilon_{it}, \varepsilon_{is}) = \begin{cases} \sigma_\varepsilon^2 & t = s \\ 0 & \forall t \neq s \end{cases}$, which implies that $E(\varepsilon_i, \varepsilon_{i'}) = \sigma_\varepsilon^2 I_T$ where I_T is identity matrix (T, T).
- $E(\varepsilon_{it}, \varepsilon_{js}) = 0$, $\forall j \neq i$, $\forall (t, s)$.

Giving theses assumptions, inserting equation [2] into equation [1] and taking logs yields the following empirical model[1]:

$$LnY_{it} = \alpha_1 LnL_{it} + \alpha_2 LnICT_{it} + \alpha_3 LnK_{it} + \mu_{it} \qquad [3]$$

$$\mu_{it} = \gamma_t + \eta_i + \varepsilon_{it}$$

In addition to the previous hypotheses on ε_{it}, we are willing to make some other technical hypotheses on the structure of the residuals. We assume that μ_{it} are satisfying the following conditions $\forall i \in [1, N]$ and $\forall t \in [1, T]$:

- $E(\eta_i) = E(\gamma_t) = E(\varepsilon_{it}) = 0$
- $E(\eta_i \gamma_t) = E(\gamma_t \varepsilon_{it}) = E(\eta_i \varepsilon_{it}) = 0$

[1] We omit a constant because it would be collinear with η_i .

- $E(\eta_i \eta_j) = \begin{cases} \sigma_\eta^2 & i = j \\ 0 & \forall i \neq j \end{cases}$
- $E(\gamma_t \gamma_s) = \begin{cases} \sigma_\gamma^2 & t = s \\ 0 & \forall t \neq s \end{cases}$

The problem now is to obtain consistent estimates for the parameter vector $(\alpha_1, \alpha_2, \alpha_3)$.

III- GMM-SYS estimator

The GMM-SYS estimator is our preferred estimator because it helps solve most of the shortcomings of conventional estimators (OLS, WITHIN and first difference GMM). To get a clear picture, let us consider the model [3] above:

The main disadvantage of OLS estimates of the parameter vector $(\alpha_1, \alpha_2, \alpha_3)$ is that explanatory variables are correlated with the error term μ_{it} due to the presence of individual specific term, and this correlation does not vanish as the number of individual units in the sample gets larger (see Bond, 2002).

Taking the equation [3] in first difference help remedy the problem of unobserved heterogeneity since it swept η_i from the model. In fact, given that $\eta_{i,t} - \eta_{i,t-1} = 0$, we obtain:

$$\Delta y_{it} = (\gamma_t - \gamma_{t-1}) + \tilde{\alpha} \Delta X_{it} + (\varepsilon_{it} - \varepsilon_{i,t-1}) \qquad [4]$$

Where LnY_{it} is replaced by y_{it} ; X is the matrix of all the explanatory variables; $\tilde{\alpha}$ is the parameter vector $(\alpha_1, \alpha_2, \alpha_3)$ and "Δ" denotes the changes from $t = 1$ to $t = 2$.

Now that the fixed-effects have been cancelled out, OLS can yield consistent estimates of $\tilde{\alpha}$ if the explanatory variables X_{it} are uncorrelated with ε_{it}. However, this is not the case since measurement errors, particularly in both types of capital are more likely, as argued by Brynjolfsson and Yang (1996). Moreover, simultaneity in input and output decisions is also more likely and this introduces the simultaneity bias.

In order to correct for these two potential sources of bias, the GMM estimation approach is applied for the equation [4] in first difference. This approach takes advantage of the panel structure of data by instrumenting contemporaneous inputs in first difference by their lagged values in the past. Specifically, Arellano and Bond (1991) proposed to use the corresponding levels of the lagged inputs X_{t-2}, X_{t-3}, X_{t-4} ….. X_0 to instrument endogenous inputs at the right-hand side of equation [4], leading to the following moment condition:

$$E\left[X_{i,t-s}.\left(\varepsilon_{it}-\varepsilon_{i,t-1}\right)\right]=0 \text{ for } s=1,2\ldots\ldots\ldots T. \qquad [5]$$

Equation [5] shows that there are more valid instruments than endogenous variable and this is the main advantage of GMM estimator over the standard Instrumental Variable[2] estimator.

However, lagged levels of the variables may not be good instruments of current differences if the series are persistent over time as is usually the case with capital stocks. In fact, in such a case, the correlation of the first differences with the second lag is close to zero.

Blundell and Bond (2000) showed that the problem of weak instruments may introduce some bias and imprecision in first difference GMM estimates. They argued that this poor performance could be dramatically counteracted by incorporating more informative moment conditions that are valid under the stationarity of the series. Basically, this results in the estimation of a system of two equations, the first being the differenced equation in [4] and the second being the level equation in [3]. Suitable lagged levels of X_{it} are used as instruments in the first differenced equation while lagged-first differences are used as instruments in levels equations[3].

The validity of GMM estimates depends upon the validity of moment conditions and the validity of the assumption that ε_{it} are serially uncorrelated. When GMM-SYS is used, a Sargan Difference test should be examined to see if there is evidence that the additional moment conditions are valid. If not, first difference may be preferred[4]. Under the null hypothesis that moment conditions are valid, the test statistic is asymptotically distributed as chi-squared. In addition, the LM test of serial correlation should be examined. There should be significant first order correlation of the first order residuals and no second order correlation.

[2] See Anderson and Hsiao (1982).
[3] See Arellano and Bover (1995).
[4] Blundell and Bond (2000) reported that in many contexts, additional moment restriction exploited by the GMM-SYS estimator appear to be valid though, and they appear to be useful in reducing biases associated with first-difference.

IV- Data

The data we use are from the short-term trends survey conducted by the Department of Forecasting at the Ministry of Economy and Finance, Cameroon. The dataset contains quarterly data on sales, number of employees, expenditures for gross investment for 60 firms since 2000. It does not contain expenditures for ICT-capital. However, it has been possible to obtain that information by sending a request to the enterprises of the sample, asking them to declare the amount spent in ICT equipment since 2000. After taking in account non-responses and inconsistencies in some reports, we obtain a balanced panel of 47 firms observed for 4 years (2003-2006).

An important issue in our empirical work is the construction of both types of capital stocks. Investment in conventional capital is defined as total investment expenditures minus ICT investments as reported by the firms. Both types of capital stock and employment are measured at the end of the firm's accounting year. Further details on the data construction can be found in Hempell (2002).

V- Estimation results

In this section, the most suitable system GMM estimator is applied to obtain consistent estimates of model [3]. The first-differenced GMM estimator is also applied to investigate and illustrate the problem of weak instruments in first-differenced equations as discussed above. All regressions were computed using the DPD98 program developed by Arellano and Bond (1998) running in GAUSS.

We take as instruments the lagged levels dated t-2 and t-3 in first-differenced equations. As additional instruments in the system GMM estimation, we take the lagged differenced dated t-1. Time dummies have been included in the model. We report results for the two-step GMM estimator for both the first- differenced equations and the system.

<u>Table 1:</u> GMM estimation results

	GMM-DIF		GMM-SYS	
	Coef.	P.values	Coef.	P.values
Employment	-0.476739	0.522308	0.177872	0.003990
ICT –Capital	-0.017403	0.958129	-0.453649	0.017620
Conventional-capital	0.872597	0.007564	0.910749	0.000000
M1	-	0.007	-	0.065
M2		0.105		0.251
Sargan		0,424		
Dif-Sargan				0.561

Source: Authors' computations using the DPD98 program

The first-differenced GMM estimation provides a negative though non significant coefficient for the ICT-capital. The specification tests do not provide evidence against the model. First, the orthogonality conditions in the first-differenced equations with lagged levels dated t-2 and t-3 are accepted as indicated by the p-value of the Sargan test of overidentifying restrictions. Second, the first and second serial autocorrelation tests (M1 and M2) are consistent with the serially uncorrelated error term we have assumed for the model [3].

However, weak instruments are a potential problem when relying on first-differenced GMM estimators. Therefore, they may be important finite sample bias affecting the differenced GMM results.

To investigate this, let us consider the reduced form of the endogenous series of equation [4] expressed as:

$$\Delta X_{i2} = \pi X_{i1} + r_i \text{ for } i = 1.........N \qquad [6]$$

If the instruments used in the first-differenced equations are to be weak, then Blundell and Bond (2000) showed that the least squares estimates of the reduced form coefficient π can be made arbitrarily close to zero.

We obtain estimates of the reduced form coefficient for the three series: employment (l_{it}); ICT-capital (ict_{it}) and conventional-capital (k_{it}). The results are reported in table 2 below:

Table 2: Estimates of the reduced form of the simple AR (1) specifications for the series

Variable	Employment	ICT-capital	Conventional-capital
π	0.029446	-0.126001	-0.096701
(Std. error)	(0.024347)	(0.055645)	(0.055416)

Source: Authors' computations using the DPD98 program

As expected, all the three series are found to be highly persistent. These results suggest that the first-differenced GMM estimates reported in table 1 should be biased. Similar results have been found in different contexts such as labour demand equation and investment equation among others (see Blundell and Bond, 2000).

Applying the extended GMM estimator, we obtain a great improvement in terms of efficiency: the precision of all the estimates improves considerably and the coefficient of employment becomes positive. The Difference Sargan test does not reject the additional orthogonality conditions associated with levels equations with lagged differences as instruments. Also, the first and second serial autocorrelation tests (M1 and M2) are consistent with the serially uncorrelated error term we have assumed for the model [3].

The system GMM estimates of the parameters of model [3] appear to be reasonable. Particularly, concerning the central issue of this paper, the negative and significant estimated coefficient of ICT-capital allows us to argue that, in average, Cameroonian firms are not realising the productivity gains from ICT. This result recalls the productivity paradox (Solow, 1987), but the real question is how it can be understood in the present context.

VI – Some possible explanations

Beyond the constraints at macro-level, a wide-range of studies argues that ICT requires significant workplace and labour reorganization at firm-level in order to be productive. ICT is only a small component of a complex set of causalities (skills, infrastructures, organization, diffusion, adoption, adaptation, etc.) which include both tangibles and intangibles aspects. If such complete cluster of associate complements does not improve together, some ICT benefits may be lost and ICT becomes mainly a cause of higher costs rather than improving output (Atzeni and Carboni, 2005).

This would suggest that Cameroonian firms still need to take adequate measures to reap the productivity gains of ICT. Further research might try to point out precisely critical factors influencing the impacts of ICT on productivity. This would enhance our understanding of the ways in which ICT affects productivity and contribute to solve the productivity paradox that continues to provoke discussions in empirical research on developing countries[5].

However, the result may also come from bias in the econometric estimation, which is a result of the peculiarities of ICT. Firm-level studies on ICT impacts on productivity use various methods[6], and empirical evidence would be stronger if it can be confirmed by different methods.

VII- Conclusion

The aim of this paper was to provide a robust estimation of the impact of ICT on Cameroonian firms' productivity using panel data. Our findings suggest that finite sample bias due to weak instruments is a potential problem when relying on first-differenced GMM estimator. The application of the extended GMM estimator, with more informative instruments, improves the efficiency of estimates and gives more reasonable results.

We find that, in average, ICT has a negative significant impact on firms' productivity in Cameroon. However, this shortfall of evidence is not necessarily and evidence of shortfall. In fact, our model is limited in nature as it does not takes explicitly into account other critical factors that influencing the impacts of ICT on productivity. This opens an avenue for future research in order to throw more lights on the way in which ICT may impact productivity at firm level.

[5] See for example Chowdyury and Wolf (2006) who have also found a negative impact of ICT investments on labour productivity in Small and Medium enterprises in East Africa.
[6] See OECD (2003b) for a synthesis.

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