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CAPITAL OPERATING TIME AND WORKING TIME IN THE PRODUCTION FUNCTION: AN EVALUATION ON A PANEL OF FRENCH FIRMS OVER THE PERIOD 1989-2001

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Abstract

While a number of studies have demonstrated the importance of factor utilization in economic analysis, the impact of operating hours and/or hours of work in the production function remains largely unknown, particularly in terms of the capital operating time. Using French data on industrial firms for the period 1989 to 2001, we estimate a Cobb-Douglas production function that considers the stocks and both the capital operating time and the working time. We draw on the framework defined by Blundell and Bond (2000), assuming that serially correlated shocks allow a dynamic representation of the production function, and we use the system generalized method of moments for estimation. Splitting capital operating time into shiftwork patterns and working time, our results show that shiftwork patterns matter for the estimation of a production function while working time is less informative. Specifically, our estimates yield identical output elasticities for shiftwork and capital: thus, doubling the shifts is equivalent to doubling the stock of capital. In addition, we cannot reject the hypothesis of constant returns to scale and the Cobb-Douglas specification is accepted when taking into account the capital operating time and/or the working time. Otherwise, a Translog production function is more appropriate.

Keywords: Production function; Panel data; Generalized method of moments; Capital operating time; Working time
JEL classification: C33, D24, J23

1. Introduction

Since the beginning of the 1960s, numerous studies have addressed the importance to economic analysis of factor utilization*,* both for the analysis of factor demands (Ball and St. Cyr, 1966; Brechling and O'Brien, 1967; Nadiri, 1968; Nadiri and Rosen, 1969 and 1973) and fluctuations in productivity (Foss 1963) or for formalizing relationships in the input mix (Feldstein, 1967; Craine, 1973; Leslie and Wise, 1980; Hart and McGregor, 1987).

Although all of these studies demonstrate the importance of factor utilization to economic analysis, none has used the factor utilizations to estimate a production function at the firm level. Furthermore, while it is generally acknowledged that the two primary dimensions of factor utilization are intensity and duration (Cette and Bosworth, 1995) – the intuition being that the services provided by factors of production depend on how intensely and how long they are used – the impact of operating hours and hours of work in the production function remains largely overlooked. This oversight appears particularly unfortunate for France, where both capital operating time and working time have changed considerably in recent years. In this paper, we estimate, for the first time, a production function incorporating capital operating time and working time using firms panel data in the case of France.[1]

Our contribution is both empirical and methodological. On the one hand, we derive a general specification for a Cobb-Douglas production function incorporating working time and shiftwork[2] using the framework of Blundell and Bond (2000). We also extend this approach to a "flexible" Translog production function. On the other hand, we highlight the standard problems encountered in the literature and suggest, as in Blundell and Bond (2000), and Blundell, Bond, and Windmeijer (2000), to exploit the better finite sample properties of the system GMM (GMMS) estimator developed by Arellano and Bover (1995), and Blundell and Bond (1998). In the presence of unobserved heterogeneity and simultaneity, ordinary least squares (OLS) and Within estimators generally prove unsatisfactory. In this case, although the first-differenced generalized method of moments (GMMD) is frequently used, the properties of this estimator are quite weak when*,* for example, the variables are strongly persistent. The basic idea is thus to

[1] Note that it has not yet been done, to our knowledge, for another country at the firm level.

[2] We define capital operating time as the product of working time by a shiftwork indicator synthesizing shiftwork patterns at the firm level.

estimate a system of equations in both first-differences and levels, where instruments used in levels equations are lagged first-differences of the series and are valid under restrictions on the initial conditions.

Furthermore, we depart from Blundell and Bond in three directions. First, we use both the operating hours and the duration of work in our production function and thus we generalize their approach. Second, we assess the robustness of our functional form by estimating a "flexible" Translog production function and by evaluating the statistical contribution of capital operating time and working time with the test proposed by Bond, Bowsher, and Windmeijer (2001). Third, unlike Blundell and Bond (2000), who use the first-step standard errors, we adopt the correction proposed by Windmeijer (2004) to obtain robust second-step standard errors.

Our primary results are as follows. First, when we divide capital operating time into a function of working time and a shiftwork indicator synthesizing the different shiftwork patterns at the firm level, the estimations reveal that the shiftwork indicator is informative and statistically significant. Conversely, the working time variable has no explanatory power and remains statistically insignificant. This result appears to be attributable to its limited variability and to measurement errors. Second, the shiftwork indicator and the capital stock have identical output elasticities. Thus, doubling the shifts has the same impact on the output as doubling the stock of capital. Third, our empirical evidence suggests that a Cobb-Douglas production function is a correct approximation of the technology in our sample. When testing this formulation against a more general Translog specification, we find that the Cobb-Douglas formulation cannot be rejected when we take into consideration capital operating time and working time. However, the Cobb-Douglas specification is rejected if we consider a two-factor production function, e.g. with capital and labour stocks. Fourth, we also demonstrate that more plausible results can be achieved using the GMMS estimator. This estimator exploits stationary restrictions that remain informative even for persistent series as in our sample, and Monte-Carlo simulations show that it performs better than other "standard" panel data estimators widely used to estimate production functions in the literature. It also confirms the GMMD estimator can be poorly behaved especially when the series are highly persistent since lagged levels of series thus provide only weak instruments.

This paper is organized as follows. In section 2, we review the primary fields of economic analysis in which considering factor utilization seems most necessary. In section 3, we present the data. In section 4, the theoretical framework and the methodology are explained. In section 5, we discuss the results of the estimations. In section 6, we show that the Cobb-Douglas specification is a good approximation of the true technology in our sample. Finally, concluding remarks are in section 7.

2. Factor Utilization and Analysis of the Input Mix

The incorporation of factor utilization into economic analysis is based on the intuition that the services provided by factors of production depend on how intensely and how long they are used.

Several studies have addressed the importance of factor utilization for analyses of both factor demands and short-term productivity fluctuations or the input mix (Ball and St. Cyr, 1966; Brechling and O'Brien, 1967; Nadiri, 1968). Therefore, by creating a theoretical link between traditional factor-demand models and factor utilization, the model developed by Nadiri and Rosen (1973) made a significant contribution to economic theory. Estimations of the factor-demand model reveal that, in response to cyclical fluctuations in demand, adjustments to the desired levels occur more quickly for factor utilization than for stock variables. Several studies performed on French data that drew on this work also emphasized the impact of factor utilization (Cette, 1983; Cueva *et al.*, 1993; Cueva, 1995). Analyses of long-term productivity changes also benefited from inclusion of variations in the capital utilization. Foss's (1963) pioneering work revealed a significant positive contribution of the capital utilization to the evolution of productivity growth in the United States. In France, Cette (1990) underscored the cyclical profile of capital operating time and its consequences for the apparent productivity of capital.

On the other hand, including factor utilization in production functions is also important: adjustments to factor stocks take time while the extent to which they are used can vary rapidly. Several studies on data from the United States (Craine, 1973), the United Kingdom (Feldstein, 1967; Leslie and Wise, 1980), Germany (Hart and McGregor, 1987), and France (Cueva and Heyer, 1997; Heyer, 1998) have estimated production functions incorporating factor utilization. In France, the policy of working time reduction stimulated reflection on the role of factor utilization in the economy (Cahuc and Granier, 1997; Gianella and Lagarde, 1999).

However, studies that have validated the importance of factor utilization in economic analysis have rarely considered the capital utilization. This imbalance is illustrated in Table 1, where estimation results for a Cobb-Douglas function incorporating factor utilization are summarized. Moreover, even when capital utilization is included in the production function, heterogeneous indicators are used: some studies have used measures of capital utilization while others retained a utilization rate that is nearer to an intensity of use. Thus, the capital operating time is rarely used. Furthermore, the only study integrating both operating hours and hours of work into a production function (Cueva and Heyer, 1997) was conducted on macrosectoral data and yielded unsatisfactory results. The output elasticity of capital operating time shows little significance and the output elasticity of capital exceeds the output elasticity of labour.

Table 1 : Estimates of a Cobb-Douglas with Factor Utilization in the Literature

	β_K	β_L	β_{DHT}	β_{NOP}	Methodology	Data
Feldstein (1967)	0.26 *(0.01)*	0.73 *(0.009)*	1.71 *(2.19)*		Instrumental variables	Panel "Industry", The United Kingdom
Craine (1973)	-0.07 *(0.07)*	0.80 *(0.04)*	1.98 *(0.13)*		OLS	Panel "Industry", The United States
Leslie and Wise (1980)	0.24 *(0.01)*	0.78 *(0.01)*	1.61 *(0.18)*		OLS	Panel "Industry", The United Kingdom
Leslie and Wise (1980)	0.32 *(0.03)*	0.64 *(0.04)*	0.64 *(0.11)*		OLS (sectorial fixed effects)	Panel "Industry", The United Kingdom
Anxo and Bigsten (1989)	0.56 *(0.09)*	0.61 *(0.02)*			Instrumental variables	Panel "Industry", Sweden
Anxo and Bigsten (1989)	0.46 *(0.02)*	0.68 *(0.014)*	0.98 *(0.12)*		Instrumental variables	Panel "Industry", Sweden
Anxo *et alii* (1989)	0.51 *(0.02)*	0.63 *(0.014)*	0.91 *(0.15)*	-0.21* *(0.08)*	Instrumental variables	Panel "Industry", Sweden
Hart and Mac Gregor (1988)	0.47 *(0.20)*	0.73 *(0.16)*	0.55 *(0.15)*		Instrumental variables	Panel "Industry", Germany
Hart and Mac Gregor (1988)	0.73 *(0.16)*	0.31 *(0.12)*	0.82 *(0.36)*	0.32 *(0.01)*	Instrumental variables	Panel "Industry", Germany
Cueva and Heyer (1997)	0.19 *(0.12)*	0.72 *(0.11)*	1.54 *(0.47)*		OLS	Sectoral Panel, France
Cueva and Heyer (1997)	0.73 *(0.11)*	1.89 *(0.50)*	0.88 *(0.10)*	1.59** *(0.87)*	OLS	Sectoral Panel, France
Gianella and Lagarde (1999)	0.21 *(0.00)*	0.83 *(0.00)*	0.22* *(0.10)*		OLS	Sectoral Panel, France
Gianella and Lagarde (1999)	0.19 *(0.08)*	0.83 *(0.10)*	0.88* *(1.82)*		GMMS	Sectoral Panel, France
Blundell and Bond (2000)	0.23 (0.07)	0.77 (0.09)			GMMS	Panel "Industry", The United Kingdom

Note : Standard deviations parentheses
* capital utilization is approximated by the utilization capacity rate.
** denotes that the coefficient is not significant at the 10% level.

In this respect, using firm-level data is of particular interest for analyzing working time and capital operating time. Their greater variability along with their microeconomic character give panel data a clear edge over aggregate macroeconomic series for studying the choices and behaviour of firms. However, to our knowledge, there are no studies on individual data that estimate a production function including both capital operating time and working time.

There appears to be two reasons for this lack, at least in the case of France. The first is the absence of data on capital operating time. The second reason relates to the difficulty of estimating a production function on individual data. Considering simultaneity bias and unobserved heterogeneity generally yields particularly disappointing results. Thus, as emphasized by Griliches and Mairesse (1997), "In empirical practice, the application of panel methods to micro-data produced rather unsatisfactory results: low and often insignificant capital coefficients and unreasonably low estimates of returns to scale."

Nonetheless, (i) Blundell and Bond (2000) define a formal framework allowing the estimation of a Cobb-Douglas type production function which yields particularly interesting results, and (ii) we are able to combine two databases of the Banque de France to obtain factor stocks and durations of utilization at the firm level.

Having overcome these two limitations, we propose the first estimation of a Cobb-Douglas type production function including capital operating time and working time.

3. The Data

The sample used for the estimations was generated by combining two of the Banque de France's data files: data from the Balance-Sheet Data Office and the Annual Survey of Capital Operating Time in Industry.[3]

- The dependent variable, Y, is real value added at factor cost. It is computed using accounting data from the Balance-Sheet Data Office.
- Owing to the absence of information on the evolution of equipment efficiency over time (OECD 2001), the capital stock considered is the gross capital stock. It is computed using

[3] See Appendix 1.

accounting data from the Balance-Sheet Data Office and the Perpetual Inventory Method. We consider a constant rate of depreciation.

- The annual survey of capital operating time (COT survey) provides the total workforce (L) as well as the shiftwork patterns at the firm level. This allows computation of a synthetic shiftwork indicator (NOP) which provides the capital operating time (DUE) when combined with working time according to the following relationship:[4]

$$DUE = NOP \times DHT \ .$$

Despite its reliance on strong assumptions, this type of measure for the operating hours is widely used in empirical analyses (Cette and Bosworth, 1995). In our case, this formulation also allows estimation of the output elasticity of working time and shiftwork.[5]

- Working time at the firm level comes from the COT survey. With regard to this latter variable, we cannot discount the possibility that it may be imperfectly measured. Aggregate results obtained from this variable resemble those from the Acemo-Dares survey, suggesting that it may also overestimate the decline in hours worked (Dares 2001). Indeed, firms are canvassed on a weekly basis: agreements that affect working time and overtime may not be taken into consideration.

Combining these two sources yields an unbalanced panel of 386 industrial firms covering all or part of the period 1989–2001. Overall, 2.493 observations are present in our sample.[6]

4. The Estimated Relationships and the Estimation Methodology

4.1 Parameter estimates for the production function

In keeping with the literature on factor utilization, we assume that output depends on the services of labour (*SL*) and of capital (*SK*). For the sake of simplicity, and since it is commonly used in the literature and seems to provide a good approximation to the structure of a two-factor production function (Hamermesh, 1993), a Cobb-Douglas specification is assumed. In Section 6, to assess the robustness of our results, we estimate a “flexible” Translog production function and

[4] See Appendix 1 for a definition of shiftwork.

[5] Retaining a synthetic measure for *DUE* does, in fact, lead to the problem of estimating the elasticity of hours of work, since *DUE* depends directly on this value.

[6] Descriptive statistics are not included here but are available from the authors.

test our specification against this more general specification. Therefore, we seek to estimate the following relationship:

$$Y_{i,t} = SL_{i,t}{}^{\beta_L} \times SK_{i,t}{}^{\beta_K} \qquad (1)$$

with $Y_{i,t}$ representing the *real* value added at factor cost for firm i at time t, and $SL_{i,t}$ and $SK_{i,t}$ the services supplied by labour and capital, and $\beta_L \leq 1$; $\beta_K \leq 1$.

We further assume that the services provided by a factor depend upon its stock and duration of utilization, and can be expressed as:

$$SK = K \times DUE^{\alpha_{DUE}} \qquad (2)$$

and

$$SL = L \times DHT^{\alpha_{DHT}}\ , \qquad (3)$$

where L represents the workforce, K the *stock* of capital, DHT the working time, and DUE the capital operating time. We also assume that α_{DUE} and $\alpha_{DHT} \leq 1$, allowing the possibility of decreasing returns in the use of capital and labour.

Combining equations (2) and (3) yields:

$$Y_{i,t} = L_{i,t}{}^{\beta_L} \times K_{i,t}{}^{\beta_K} \times DHT_{i,t}{}^{\beta_L \times \alpha_{DHT}} \times DUE_{i,t}{}^{\beta_K \times \beta_{DUE}}\ . \qquad (4)$$

Note that in the context of a production function including factor utilization such as equation (4), the notion of constant returns to scale pertains only to stocks (Nadiri and Rosen, 1969). Hence, returns to scale will be constant if, holding factor utilization unchanged, doubling stocks of capital and labour yields twice the output.[7]

If we now assume that the capital operating time is the product of working time by a shiftwork indicator reflecting the development of shiftwork within the firm (NOP), we obtain:

$$Y_{i,t} = L_{i,t}{}^{\beta_L} \times K_{i,t}{}^{\beta_K} \times DHT_{i,t}{}^{\beta_{DHT}} \times NOP_{i,t}{}^{\beta_{NOP}} \qquad (5)$$

with $\beta_{DHT} = \beta_L \times \alpha_{DHT} + \beta_K \times \beta_{DUE} \leq \beta_L + \beta_K$; $\beta_{NOP} = \beta_K \times \alpha_{DUE} \leq \beta_K$.

After taking logs in equation (5) (lowercase variables indicate logs) we obtain:

$$y_{i,t} = \beta_L \times l_{i,t} + \beta_K \times k_{i,t} + \beta_{NOP} \times nop_{i,t} + \beta_{DHT} \times dht_{i,t}\ . \qquad (6)$$

Drawing on the framework defined by Blundell and Bond (2000), the relationship to be estimated assumes the following form:

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[7] This assumption guarantees consistency when only factors stocks are considered, since then, the stability of factor utilization is implicitly assumed.

$$y_{i,t} = \beta_L \times l_{i,t} + \beta_K \times k_{i,t} + \beta_{NOP} \times nop_{i,t} + \beta_{DHT} \times dht_{i,t} + \mu_t + \delta_s + (\eta_i + v_{i,t} + m_{i,t}), \qquad (7)$$

with γ_t a time-specific effect and δ_s a sector-specific effect.

The error term consists of three effects: η_i is a firm-specific effect, $v_{i,t}$ is a first-order autoregressive shock ($|\rho|<1$), and $m_{i,t}$ captures measurement errors, if any:

$$\begin{aligned} v_{i,t} &= \rho \times v_{i,t-1} + e_{i,t} \\ e_{i,t}, m_{i,t} &\sim MA(0). \end{aligned} \qquad (8)$$

Incorporating an autoregressive error term into the global error term thus yields a dynamic relation.[8] Indeed, from equations (7) and (8), we can write:

$$\begin{aligned} y_{i,t} &= \rho y_{i,t-1} + \beta_L \left(l_{i,t} - \rho l_{i,t-1}\right) + \beta_K \left(k_{i,t} - \rho k_{i,t-1}\right) + \beta_{NOP} \left(nop_{i,t} - \rho nop_{i,t-1}\right) \\ &+ \beta_{DHT} \left(dht_{i,t} - \rho dht_{i,t-1}\right) + (\gamma_t - \rho \gamma_{t-1}) + \delta_s (1-\rho) + (\eta_i (1-\rho) + e_{i,t} + m_{i,t} - \rho m_{i,t-1}) \end{aligned} \qquad (9)$$

or

$$\begin{aligned} y_{i,t} &= \pi_1 y_{i,t-1} + \pi_2 l_{i,t} + \pi_3 l_{i,t-1} + \pi_4 k_{i,t} + \pi_5 k_{i,t-1} + \pi_6 nop_{i,t} + \pi_7 nop_{i,t-1} \\ &+ \pi_8 dht_{i,t} + \pi_9 dht_{i,t-1} + \gamma_t^* + \delta_s^* + \eta_i^* + w_{it} \end{aligned} \qquad (10)$$

such that:

$$\pi_3 = -\pi_2 \pi_1, \; \pi_5 = -\pi_4 \pi_1, \; \pi_7 = -\pi_6 \pi_1 \text{ and } \pi_9 = -\pi_8 \pi_1. \qquad (11)$$

It is important to note that the error term w_{it} is an $MA(0)$ process if there is no measurement error, and an $MA(1)$ process if the variance of the error term is not nil.

Therefore, estimation of the output elasticities requires several steps. We estimate first Eq. (10) and test whether the common factor restrictions (11) are binding. These restrictions can then be imposed using minimum distance to obtain the restricted parameter vector.

4.2. The estimators

Estimating a production function on firm-level data creates several problems when we allow for unobserved heterogeneity and examine the finite sample properties of the standard estimators. As Griliches and Mairesse (1997) emphasize, the OLS estimator provides plausible parameter estimates for the factors' shares in the economy, and these are generally consistent with the assumption of constant returns to scale. In the presence of unobserved heterogeneity and

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[8] An identical formulation is obtained by assuming that global factor productivity follows a stationary process (Dupaigne 2002).

simultaneity, however, the performance of this estimator becomes somewhat less impressive.[9] In the same vein, the Within estimator generates unsatisfactory and downwardly biased estimates, especially to the extent that the time dimension is small relative to the cross-section dimension, which is often the case in microeconomic panels (Anderson and Hsiao, 1981; Nickell, 1981).

In this context, the GMMD, which eliminates unobserved individual effects by taking first differences, should yield more satisfactory results. This estimator can be described as follows.

Assume that equation (9) satisfies the following conditions (Blundell and Bond, 2000):

(i) $E[z_{i,t}\chi] \neq 0$,

where $z_{i,t} = l_{i,t}, k_{i,t}, nop_{i,t}, dht_{i,t}$ and $\chi = \eta_i, e_{i,t}, m_{i,t}$, respectively;

(ii) $E[\eta_i] = 0, E[v_{i,t}] = E[m_{i,t}] = 0, E[v_{i,t}\eta_i] = E[m_{i,t}\eta_i] = 0$

$\forall\ i = 1,\dots,N$ and $\forall\ t = 2,\dots,T$;

(iii) $E[m_{i,t}m_{i,s}] = 0$

$\forall\ i = 1,\dots,N$ and $s \neq t$;

(iv) $E[v_{i,t}m_{i,s}] = 0$

$\forall\ i = 1,\dots,N$ and $\forall\ t = 1,\dots,T$;

(v) $E[v_{i,t}v_{j,t}] = 0, E[m_{i,t}m_{j,t}] = 0$

$\forall\ i = 1,\dots,N$ and $j \neq i$;

(vi) $E[y_{i1}v_{i,t}] = E[y_{i1}m_{i,t}] = E[x_{i1}v_{i,t}] = E[x_{i1}m_{i,t}] = 0$

$\forall\ i = 1,\dots,N$ and $\forall\ t = 2,\dots,T$.

Condition (i) captures any eventual correlation between the explanatory variables and the individual effect, the autoregressive error term, and the measurement error. Condition (ii) establishes that the individual effect, the autoregressive term, and the measurement error have a zero mean and that the error terms are not correlated with the individual effect. Condition (iii) implies that the measurement error is not serially correlated. Condition (iv) assumes that the autoregressive error and the measurement error are not correlated. Condition (v) means that the

[9] For instance, Marschak and Andrews (1944) demonstrate that the exogenous variables cannot be considered independent and that the assumption of exogeneity no longer obtains if we consider the choice of production factors to be the result of profit maximization by the firm.

measurement errors and the autoregressive errors of two different firms are not correlated at time *t*. Finally, condition (vi) imposes that the initial conditions for the dependent variable and the explanatory variables are predetermined.

Conditions (vi) yield the following moment conditions:

$$E[\tilde{x}_i^{t-s}\Delta w_{i,t}]=0\,,$$

where

$$\tilde{x}_i^{t-s}=(1,x_i^{t-s})$$
$$x_i^{t-s}=(x_{i,1},...,x_{i,t-s})$$
$$x_{i,s}=(y_{i,s},k_{i,s},l_{i,s},nop_{i,s},dht_{i,s})$$

with $s\geq 2$ when $w_{i,t}\sim MA(0)$ and $s\leq 3$ when $w_{i,t}\sim MA(1)$.

Therefore, suitable lagged variables in levels serve as instruments in the first-difference equations. These conditions can be written more compactly as:

$$E[Z_i'\Delta w_i]=0\,, \qquad \text{(M1)}$$

where $\Delta w_{i,t}=(\Delta w_{i,s},...,\Delta w_{i,T})'$ and Z_i is the matrix of level instruments.

The GMMD estimator is thus consistent when $N\to\infty$ and *T* is fixed. However, this estimator has weak finite sample properties. In particular, on the basis of Monte Carlo simulations, Arellano and Bond (1991), Kiviet (1995), Ziliak (1997), and Blundell and Bond (1998), among others, show that the GMMD estimator may be severely biased when (a) *N* is finite and *T* is small, (b) the number of moments is relatively large compared to the cross-section dimension, and (c) the instruments are weak in the sense of Staiger and Stock (1997). In addition, Alvarez and Arellano (2003) derive the asymptotic bias under more general assumptions. All these results pertain to a simple autoregressive model without explanatory variables. The inclusion of explanatory variables may reduce this bias. Similarly, when the explanatory variables (and the dependent variable) are highly persistent (possibly following a random walk), Blundell and Bond (2000) draw attention to the bias and imprecision of the GMMD estimator.[10]

[10] The difficulty here is to establish the size of the finite sample bias. A simple method consists of comparing the GMMD estimator with the OLS and Within estimators. In the framework of a first-order autoregressive model (without explanatory variables), Hsiao (1986) shows that the OLS estimator is biased upwards, while Anderson and Hsiao (1981) and Nickell (1981) demonstrate that the Within estimator is biased downwards (when the time dimension is small). In addition, a consistent estimator of the autoregressive term (ρ) should lie between these two limiting cases. Consequently, if GMMD estimates are near to, or below, Within estimates, we can conclude that the estimations are biased, because of weak instruments, for example. Sevestre and Trognon (1996) demonstrate that

The possibility that GMMD estimations might introduce a non-negligible bias into our study thus led us to choose the GMMS method, especially since Mairesse and Hall (1996) show that the GMMD estimator does not yield significantly better results in the case of a production function, while Blundell, Bond, and Windmeijer (2000) demonstrate that the GMMS estimator yields highly significant increases in precision and also substantially cuts the sampling bias in comparison with the GMMD estimator when the regressors are weakly exogenous and correlated with the individual effect.[11]

Indeed, in the case of strongly persistent series, Arellano and Bover (1995) and Blundell and Bond (1998, 2000) illustrate that it is preferable to use a GMMS estimator.[12] This involves combining the GMMD estimator with additional conditions on the equations in levels. Assume that the following conditions hold:

(i) $E[\Delta k_{i,t}\eta_i^*] = E[\Delta l_{i,t}\eta_i^*] = E[\Delta nop_{i,t}\eta_i^*] = E[\Delta dht_{i,t}\eta_i^*] = 0$;

(ii) $E[\Delta y_{i,2}\eta_i^*] = 0$.

The first condition establishes that the explanatory variables in first differences (except the dependent variable in lagged first differences) are not correlated with the individual effect. The second condition specifies that the dependent variable in first differences at $t = 2$ is not correlated with the individual effect.

These assumptions imply the additional moment conditions:

$$E[(\eta_i^* + w_{i,t})(1, \Delta x_{i,t-s})] = 0 \qquad \text{(M2)}$$

with $s = 1$ when $w_{i,t} \sim MA(0)$ and $s = 2$ when $w_{i,t} \sim MA(1)$.

Therefore, suitable lagged first differences of the variables are used as instruments for the equations in levels (M2). These moment conditions $E[(\eta_i^* + w_{i,t})\Delta x_{i,t-s}] = 0$, however, are valid under certain assumptions on the initial observations (Arellano and Bover 1995, Arellano,

these results also obtain when there are explanatory variables (except the lagged dependent variable) that are not correlated with the individual effect and are strictly exogenous with respect to $w_{i,t}$.

[11] For the finite sample properties, see section 4.4.

[12] There are other method-of-moment-based estimators in the literature that may perform better than the GMMS estimator, as for instance the symmetrically normalized first-differenced GMM estimator developed by Alonso-Borrego and Arellano (1999), the non-linear GMM estimator proposed by Ahn and Schmidt (1995, 1997).

2004).[13] Specifically, the joint stationary of the $y_{i,t}$ and $x_{i,t}$ processes is sufficient (but not necessary) for the validity of (M1).

As previously, the moment conditions can be written

$$E\left[Z_i^{+'} w_i\right] = 0 \qquad \text{(M2)}$$

where Z_i^+ is the matrix of first-differenced instruments.

Thus, it is possible to construct the (linear) GMMD estimator by considering the moment conditions (M1) and (M2), which simultaneously use the equations in levels and the equations in first differences. It should also be noted that only the lagged variables in first differences $t-s$ are used in the equations in levels, since the other conditions are redundant with the moment conditions. The matrix of instruments for the GMMS estimator is thus defined as:

$$Z_i^S = \begin{pmatrix} Z_i & 0 \\ 0 & Z_i^+ \end{pmatrix}.$$

The moment conditions become:

$$E[Z_i^S{}' w_i^+] = 0\,,$$

with $w_i^+ = (\Delta w_{i,s},...,\Delta w_{i,t}, w_{i,s},..., w_{i,T})'$

Using this type of estimator, Blundell and Bond (2000) obtain particularly satisfactory estimates of output elasticities for labour and capital in the framework of a Cobb-Douglas production function.

Following their framework, we use the GMMS estimator as a benchmark. To fully appreciate the results this estimator yields and to compare them with those from other methods, OLS, Within, and GMMD results are also reported.

4.3. Specification tests

We perform two Wald tests for each estimation: the first is a minimum distance test of the non-linear common factor restrictions imposed on the restricted model and the second tests the null hypothesis of constant returns to scale. The validity of the moment conditions on the

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[13] In particular, when the processes $(x_{i,t})$ and $y_{i,t}$ are jointly stationary, then the moment conditions for the equations in levels obtain. This is a sufficient, but unnecessary, condition. In our study, these conditions obtain if the

equations in levels can be tested using Sargan's (1958) standard test for overidentification, the difference Sargan test, or the Hausman test comparing the results of the GMMD and GMMS estimations (Arellano and Bond, 1991). In our study, we use the first two tests. First, Arellano and Bond (1991) suggest using the statistics m_1 and m_2 to test the null hypothesis of no correlation between the first-order (second-order) residuals of the GMMD estimator (and the GMMS estimator). Under the null hypothesis that the moment conditions obtain, the Sargan statistic (denoted s_{diff} and $s_{sy,}$, respectively, for the GMMD and GMMS estimators) is given by:

$$s = \frac{1}{N}\hat{\Delta w}' Z W_N Z' \hat{\Delta w} \underset{a}{\sim} \chi^2(m-k) \text{ under } H_0,$$

where $W_N = \left(\frac{1}{N}\sum_{i=1}^{N} Z_i'\hat{\Delta w}_i\hat{\Delta w}_i Z_i\right)^{-1}$ is the matrix of optimal weights, $\hat{\Delta w}' = (\hat{\Delta w}_1', \hat{\Delta w}_2', ..., \hat{\Delta w}_N')$ are the estimation residuals from the second step, $Z' = (Z_1', Z_2', ..., Z_N')$, m is the number of moment conditions, and k is the number of estimated parameters.

The validity of the moment conditions in the equations in levels is obtained by the difference Sargan test, defined as:

$$s_{sys} - s_{diff} \underset{a}{\sim} \chi^2(m_{sys} - m_{diff})$$

Furthermore, unlike Blundell and Bond (2000), who use the robust variances generated by the first step as robust variances of the estimator from the second step of the GMMD and GMMS estimations, we use a formula proposed by Windmeijer (2004) to correct the variances in the second step.[14]

4.4. The finite sample properties of the different estimators

This section presents the performance of the different estimators presented above for time and cross-section dimensions and for degrees of persistence of the explanatory variable and the dependent variable resembling those of the sample in our study. Indeed, the results in the literature obtain only asymptotically (see Alvarez and Arellano, 2003). In this respect, it may be

first moments of the explanatory variables (with the exception of the lagged dependent variable) are invariant with time (conditional on the time indexes).

[14] Windmeijer (2004) used Monte Carlo simulations to demonstrate that the asymptotic standard errors estimated by the two-step GMM technique can contain a significant downward bias in finite samples.

useful to compare the finite sample properties of the different estimators for *N* and *T* close to our sample[15]. To do so, we follow the procedure in Blundell, Bond, and Windmeijer (2000).

Consider the following process with a single explanatory variable:

$$y_{it} = \alpha y_{it} + \beta x_{it} + \eta_i + v_{it}$$
$$x_{it} = \rho x_{it-1} + \tau \eta_i + \theta v_{it} + e_{it}$$

where

$$v_{it} \to N(0,\sigma_v^2), e_{it} \to N(0,\sigma_e^2), \text{ and } \eta_i \to N(0,\sigma_\eta^2).$$

The initial observations are obtained from the second-order stationary conditions. The process (x_{it}) is potentially correlated with the firm-specific effects and with both the autoregressive shocks and the measurement errors $(\theta \langle 0)$. Thus, for example, if $\rho \to 1$, the process (x_{it}) is very persistent and the instruments are weak.

We assume that the following parameters are fixed in the Monte Carlo simulations[16]:

$$\tau = 0.25, \theta = -0.1, \sigma_\eta^2 = \sigma_v^2 = 1 \text{ and } \sigma_e^2 = 0.16$$

Thus, unlike Blundell, Bond, and Windmeijer (2000), we estimate the parameter *β*, as well as the two autoregressive coefficients, *α* and *ρ*. Seven cases are considered for the triplet (α, ρ, β): (0.5, 0.5,1), (0.95, 0.5, 1), (0.5, 0.95, 1), (0.95, 0.95, 1), (0.99, 0.99, 1), (0.5, 0.99, 1), and (0.99, 0.5, 1). The cross-section dimension is *N* = 200, and the results of the estimations are presented for *T* = 4, 8*,* and 12. For each case, the number of repetitions is set to 10.000 and the standard error and the square root of the mean squared error are computed for the OLS, Within, GMMD, and GMMS.[17]

Table 2 suggests the following results. When the (x_{it}) and (y_{it}) processes are not too persistent (i.e., ρ and/or *α* = 0.50, case 1, 2, 3, 6, and 7), the OLS and GMMS estimators perform better than the Within and GMMD estimators. In particular, the GMMS estimator yields better results for the three parameters, the OLS estimator tending to be upwardly biased for the

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[15] To be consistent with our estimation method, we use the same set of instruments, namely the levels of the variables y, x for t – 2 to t – 4, and the growth rates of these variables at period t – 1.

[16] We also conduct Monte-Carlo simulations for other parameter values. The main conclusions remain robust. They are not reported here but are available on request.

[17] Results for the GMM estimation in levels are not reported but are available from the authors.

parameter ρ and downwardly biased for the parameter β. This better behaviour of the OLS and GMMD estimators is even more pronounced when T is small. It should be noted that the GMMD estimator is most sensitive to biases caused by weak instruments (when ρ is close to 1) and has the highest standard errors and mean squared errors among the four estimators considered in the Monte Carlo simulations. This result can also be found in Blundell, Bond, and Windmeijer (2000).

Table 2 : Monte-Carlo Simulation Results

Coefficients		OLS	Within	GMMD	GMMS	OLS	Within	GMMD	GMMS	OLS	Within	GMMD	GMMS
		T = 12				T = 8				T = 4			
Case 1 : $(\alpha,\rho,\beta)=(0.5;0.5;1)$													
α		0.778	0.549	0.878	1.014	0.780	0.545	0.857	1.022	0.780	0.576	0.914	1.085
	Std-dev.	0.045	0.054	0.163	0.151	0.059	0.073	0.228	0.205	0.106	0.129	0.556	0.404
	RMSE	0.226	0.454	0.204	0.152	0.228	0.460	0.269	0.206	0.237	0.443	0.562	0.413
ρ		0.818	0.392	0.471	0.527	0.817	0.302	0.457	0.529	0.812	-0.092	0.449	0.541
	Std-dev.	0.010	0.020	0.049	0.034	0.013	0.027	0.070	0.045	0.022	0.040	0.181	0.101
	RMSE	0.318	0.109	0.056	0.044	0.317	0.200	0.083	0.054	0.313	0.594	0.188	0.108
β		0.761	0.343	0.491	0.500	0.761	0.240	0.485	0.500	0.762	-0.161	0.488	0.500
	Std-dev.	0.017	0.022	0.037	0.031	0.020	0.028	0.056	0.041	0.032	0.036	0.143	0.085
	RMSE	0.262	0.158	0.038	0.031	0.262	0.262	0.058	0.041	0.264	0.662	0.143	0.085
Case 2: $(\alpha,\rho,\beta)=(0.95;0.5;1)$													
α		0.685	0.617	0.833	1.067	0.689	0.658	0.877	1.087	0.644	0.717	1.016	1.134
	Std-dev.	0.050	0.056	0.174	0.153	0.064	0.080	0.219	0.206	0.112	0.142	0.578	0.420
	RMSE	0.318	0.386	0.242	0.167	0.317	0.351	0.251	0.224	0.373	0.317	0.579	0.441
ρ		0.986	0.830	0.899	0.966	0.985	0.709	0.903	0.963	0.986	0.100	0.904	0.957
	Std-dev.	0.001	0.014	0.050	0.007	0.001	0.023	0.064	0.008	0.002	0.045	0.211	0.018
	RMSE	0.036	0.121	0.072	0.017	0.036	0.242	0.079	0.015	0.036	0.851	0.216	0.019
β		0.761	0.343	0.491	0.500	0.761	0.240	0.486	0.500	0.762	-0.160	0.488	0.499
	Std-dev.	0.017	0.022	0.038	0.032	0.021	0.028	0.056	0.041	0.032	0.037	0.146	0.087
	RMSE	0.262	0.159	0.039	0.032	0.262	0.261	0.058	0.041	0.264	0.661	0.146	0.087
Case 3 : $(\alpha,\rho,\beta)=(0.95;0.95;1)$													
α		0.831	0.877	0.681	1.095	0.832	0.878	0.596	1.093	0.833	0.730	0.365	1.097
	Std-dev.	0.029	0.044	0.347	0.065	0.037	0.069	0.508	0.086	0.067	0.135	1.690	0.204
	RMSE	0.171	0.131	0.471	0.115	0.172	0.140	0.649	0.126	0.180	0.301	1.805	0.225
ρ		0.649	0.458	0.473	0.524	0.649	0.360	0.463	0.526	0.648	-0.090	0.447	0.525
	Std-dev.	0.012	0.018	0.041	0.025	0.016	0.025	0.056	0.033	0.028	0.040	0.150	0.070
	RMSE	0.150	0.046	0.049	0.035	0.150	0.142	0.068	0.042	0.151	0.592	0.159	0.074
β		0.997	0.692	0.597	0.971	0.997	0.539	0.459	0.970	0.997	-0.017	0.251	0.965
	Std-dev.	0.002	0.019	0.267	0.029	0.002	0.026	0.354	0.043	0.004	0.041	0.900	0.125
	RMSE	0.047	0.258	0.442	0.036	0.047	0.412	0.606	0.047	0.047	0.968	1.139	0.126

Case 4 : $(\alpha,\rho,\beta) = (0.99;0.99;1)$												
α	0.871	1.105	0.719	1.061	0.832	1.159	0.711	1.061	0.721	0.903	0.785	1.053
Std-dev.	0.030	0.054	0.317	0.052	0.040	0.084	0.407	0.076	0.079	0.150	0.987	0.217
RMSE	0.132	0.118	0.424	0.081	0.173	0.179	0.499	0.098	0.290	0.178	1.010	0.223
ρ	0.963	0.884	0.930	0.955	0.965	0.765	0.918	0.955	0.970	0.093	0.853	0.955
Std-dev.	0.001	0.010	0.026	0.002	0.002	0.020	0.047	0.004	0.003	0.045	0.243	0.012
RMSE	0.013	0.066	0.032	0.006	0.015	0.186	0.057	0.006	0.020	0.858	0.262	0.013
β	0.997	0.692	0.599	0.971	0.997	0.540	0.456	0.970	0.997	-0.017	0.260	0.966
Std-dev.	0.002	0.018	0.268	0.029	0.002	0.026	0.356	0.042	0.004	0.040	0.893	0.127
RMSE	0.047	0.258	0.441	0.036	0.047	0.411	0.609	0.047	0.047	0.967	1.129	0.128
Case 5 : $(\alpha,\rho,\beta) = (0.99;0.99;1)$												
α	0.905	1.224	0.647	1.013	0.863	1.267	0.607	1.010	0.752	0.938	0.604	0.999
Std-dev.	0.024	0.060	0.402	0.036	0.035	0.089	0.545	0.056	0.077	0.149	1.579	0.187
RMSE	0.098	0.232	0.535	0.038	0.142	0.281	0.672	0.057	0.260	0.161	1.629	0.187
ρ	0.991	0.922	0.983	0.990	0.992	0.803	0.974	0.990	0.993	0.110	0.897	0.990
Std-dev.	0.000	0.009	0.016	0.000	0.000	0.018	0.037	0.000	0.000	0.045	0.247	0.002
RMSE	0.001	0.069	0.017	0.000	0.002	0.188	0.040	0.000	0.003	0.881	0.263	0.002
β	1.000	0.720	0.338	1.000	1.000	0.564	0.248	1.000	1.000	-0.003	0.088	0.998
Std-dev.	0.000	0.018	0.303	0.008	0.000	0.026	0.368	0.011	0.001	0.041	0.917	0.063
RMSE	0.010	0.271	0.719	0.012	0.010	0.426	0.828	0.015	0.010	0.994	1.287	0.063
Case 6 : $(\alpha,\rho,\beta) = (0.5;0.99;1)$												
α	0.837	0.914	0.631	1.024	0.837	0.917	0.579	1.024	0.837	0.746	0.378	1.029
Std-dev.	0.026	0.043	0.412	0.051	0.034	0.069	0.590	0.067	0.062	0.134	1.889	0.138
RMSE	0.164	0.096	0.411	0.051	0.166	0.108	0.724	0.071	0.175	0.288	1.989	0.141
ρ	0.597	0.460	0.489	0.507	0.597	0.364	0.483	0.507	0.597	-0.090	0.475	0.504
Std-dev.	0.013	0.017	0.031	0.024	0.016	0.025	0.045	0.032	0.030	0.040	0.122	0.064
RMSE	0.098	0.043	0.033	0.025	0.098	0.138	0.047	0.033	0.102	0.591	0.125	0.065
β	1.000	0.720	0.345	1.000	1.000	0.564	0.247	1.000	1.000	-0.004	0.074	1.000
Std-dev.	0.000	0.018	0.306	0.008	0.000	0.026	0.372	0.011	0.000	0.041	0.939	0.060
RMSE	0.010	0.270	0.713	0.012	0.010	0.426	0.830	0.015	0.010	0.994	1.311	0.061
Case 7 : $(\alpha,\rho,\beta) = (0.99;0.5;1)$												
α	0.731	0.638	0.841	1.048	0.715	0.680	0.880	1.070	0.644	0.734	1.016	1.127
Std-dev.	0.052	0.056	0.167	0.154	0.066	0.082	0.217	0.209	0.113	0.143	0.599	0.429
RMSE	0.274	0.366	0.231	0.161	0.293	0.330	0.248	0.221	0.374	0.302	0.599	0.448
ρ	0.997	0.876	0.950	0.992	0.997	0.751	0.950	0.992	0.997	0.118	0.949	0.991
Std-dev.	0.000	0.013	0.041	0.001	0.000	0.022	0.056	0.002	0.000	0.046	0.204	0.003
RMSE	0.007	0.115	0.057	0.003	0.007	0.240	0.069	0.003	0.007	0.874	0.208	0.004
β	0.761	0.342	0.491	0.5000	0.762	0.240	0.486	0.5000	0.762	-0.160	0.490	0.499
Std-dev.	0.017	0.022	0.037	0.031	0.020	0.027	0.056	0.041	0.032	0.037	0.143	0.086
RMSE	0.262	0.159	0.038	0.031	0.262	0.262	0.058	0.041	0.264	0.661	0.144	0.086

Note : Std-dev. and RMSE stand for standard deviation and root mean squared errors.

When both processes are highly persistent (i.e., ρ and α = 0.95, 0.99, cases 4 and 5), the GMMS estimator always perform better in terms of point inference, standard error, and mean squared error. This remains the case as T decreases ($T = 4$ or 8).

Thus, the results reveal that inference on the parameter β is generally very sensitive to the persistence properties of the process (x_{it}). In particular, the standard error and the mean squared error are larger than for the other parameters. For the other two parameters, there is a non-negligible bias, depending on the case considered and the estimator used. At the same time, the precision (standard error) increases with the time dimension.

These results of the Monte Carlo simulations lead us to prefer the GMMS estimator. With this method, however, we cannot rule out the possibility that, at best, the parameter β is upwardly biased.

5. Results

5.1. Constant returns to scale and elasticity of capital near 0.3 in the case of a two-factor production function

We first estimate a production function containing only stocks of factors. For the GMMD and GMMS estimators, the levels of the variables y, k, and l for $t-3$ to $t-5$, and the growth rates for $t-2$, were used as instruments[18]. Overall, this leads to reduce the sample size to 949 observations.[19] For all models, the test for dynamic representation is statistically accepted at standard significance level (Table 3).

These initial results suggest an autoregressive coefficient that is upwardly biased for the OLS estimator and downwardly biased for the Within estimator (see Appendix 2). This is consistent with standard results in the literature and our Monte-Carlo simulations. As to the GMMD estimator, we obtain a very small and statistically insignificant autoregressive coefficient.

In keeping with the usual results obtained with OLS and Within estimators, we find output elasticities of labour and capital that are plausible (with regard to their share in the economy) and

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[18] We also conduct estimations when the instruments are lagged levels at $t-2$ to $t-4$ and growth rates at $t-1$, are presented in the Appendix 2. However, the difference Sargan test rejects the validity of these instruments.

consistent with the assumption of constant returns to scale (Table 3). The GMMD estimator yields an output elasticity of capital that is near zero and not significant. This result is similar to those in Mairesse and Hall (1996).

Table 3 : Cobb-Douglas Production Function with 2 Factors

	OLS	*Within*	GMMD*	GMMS*
β_L	0.650	0.658	0.436	0.466
	(0.057)	(0.071)	(0.221)	(0.152)
β_K	0.307	0.203	-0.111	0.422
	(0.048)	(0.065)	(0.196)	(0.163)
Constant returns to scale				
β_L	0.679	0.726	**	0.720
	(0.046)	(0.056)		(0.126)
β_K	0.321	0.274		0.280

Note : Year and sectoral dummies included in all models

* Corrected two-step standard errors in parentheses (Windmeijer, 2004)

** Results are not reported when the Wald test of the constant returns to scale hypothesis is not accepted in the restricted models.

The results from the GMMD estimation lead us to question the nature of the instruments. In particular, one condition for the parameters to be correctly identified is that the instruments be correlated with the endogenous variable in first differences. When that is not the case, the instruments are weak in the sense of Staiger and Watson (1997), and the GMMD estimator is not reliable.[20] In addition, Blundell and Bond (2000) demonstrate that when the series are strongly persistent, the instruments used to estimate the GMMD are weak and this estimator is not appropriate.

To pursue the analysis of our results more deeply, we examine the persistence properties of the various series and test the unit root hypothesis using OLS regressions. This choice is motivated by the work of Bond, Nauges, and Windmeijer (2002) in which robust micro panel

19 Thus, one limitation of our study may be that the cross-section dimension is relatively small, while the time dimension covers the entire period of the estimation for some firms.

20 The intuition is as follows. If we consider the extreme case of a random walk, there is no correlation between the variables in first differences and the lagged levels. It follows that the autoregressive parameter is not identified, the rank condition is not satisfied, and the instruments do not add any information.

unit root tests are conducted, based on (one-tailed) *t*-tests from OLS regressions. Our results indicate that the series are strongly persistent but fail to show a unit root (Table 4) [21].

Table 4 : Persistence and Unit Root Tests

	Y_t	L_t	K_t	NOP_t	Dht
Lagged variable *	0.99 (0.003)	0.99 (0.002)	0.99 (0.02)	0.90 (0.01)	0.54 (0.03)
t-test **	0.04	0.05	0.00	0.00	0.00

* Results are based on the following OLS regressions: $Z_{it} = \alpha Z_{i,t-1} + \mu_s + \eta_t + \nu_i + \varepsilon_{i,t}$, with $Z = Y, K, L, Nop, Dht$ (respectively) and μ_s are sectoral dummies (level NAF 16), and η_t are time dummies;
** t-test (p-value) : $H_0 : \alpha = 1$ and $H_1 : \alpha < 1$ (see Bond, Nauges, and Windmeijer, 2002).

Therefore, it appears more appropriate to use the GMMS estimator, which also yields a more satisfactory estimate of the autoregressive parameter[22]. The GMMS estimator yields elasticities for labour and capital that are statistically significant, on the order of 0.47 and 0.42, respectively (Table 4). These output elasticities are comparable with those obtained by Blundell and Bond (2000) using data on U.S. firms. The largest standard errors reported hereafter are those generated by the correction to the variance using Windmeijer's (2004) method. Since the assumption of constant returns to scale is accepted, we perform a constrained estimation. It yields elasticities for labour and capital that are slightly different, the output elasticity of labour being close to 0.7 and that of capital, 0.3. These results are equivalent to those obtained from the OLS and Within estimations.

5.2. Shiftwork and capital: Identical output elasticities within the production function?

We subsequently estimate a production function integrating shiftwork and working time. For the GMMD and GMMS estimators, the levels of the variables *y*, *k*, *l*, and *nop* for $t-3$ to $t-5$,

[21] However, Bond, Nauges, and Windmeijer (2002) note that the strength of this test decreases as the variance of the individual effect increases. It therefore becomes more difficult to reject H_0.

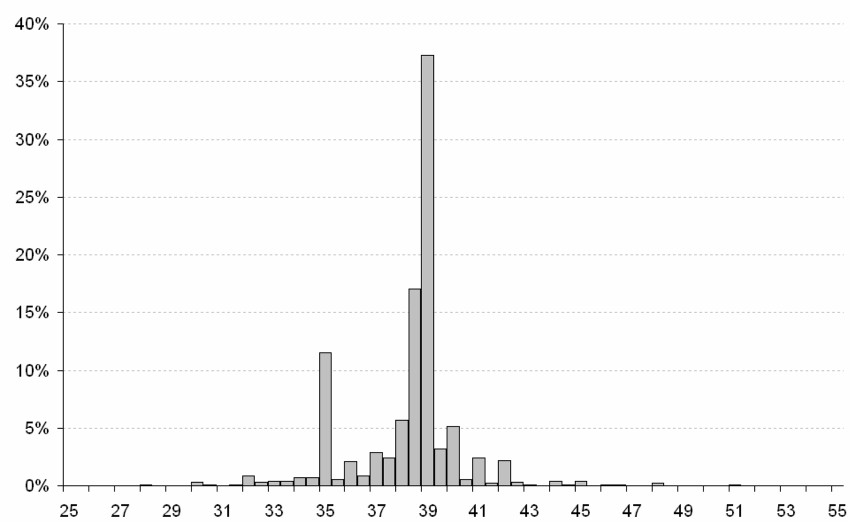
[22] The dependent variable's high degree of persistence can be mitigated by replacing the value added with the value added per unit of labour (the autocorrelation coefficient is 0.93). The results, however, are equivalent and are not presented. They can be obtained from the authors.

and the growth rates for $t-2$ are used as instruments.[23] Given the uncertainty surrounding measurements of the working time, we opt not to retain it as an instrument. As previously, the test for dynamic representation is statistically accepted for all estimations (Appendix 2). Table 4 presents the results for the various estimations.

Incorporating shiftwork and working time into the production function does not modify the output elasticities of labour or capital for the OLS, Within, and GMMD estimators. Conversely, for the GMMS estimator, the elasticity of labour reaches 0.69 and that of capital 0.35 (Table 5).

The working time proves disappointing, because, regardless of the estimator, its output elasticity is particularly small—it is only significant for the Within estimator. This result appears to be attributable to the uncertainty surrounding its measurement. In effect, this variable does not take into account potential redefinitions of the time worked resulting from the substantial reduction in working time starting in 1997, or for agreements to annualize time worked, or for overtime. The unique profile of this variable, notably its limited variance and the existence of accumulation points, also may justify our results (Figure 1).

Figure 1
Distribution of Working Time



[23] Results for y, k, l, and *nop*, when the instruments are lagged levels at $t-2$ to $t-4$ and growth rates at $t-1$ are presented in Appendix 2.

Note : 949 observations. The mean and the standard deviation are 38.30 and 2.16, respectively.

Incorporating shiftwork appears more promising. The output elasticity of shiftwork is significant for all estimators except the GMMD estimator. In the case of the GMMS estimator, the value of this elasticity is near that of capital, and we cannot statistically preclude the possibility that they are identical. This would mean that an increase in shiftwork has the same impact on production as an increase in the stock of capital.

As in the case of the two-factor production function, the assumption of constant returns to scale is accepted for all estimators except the GMMD. The imposition of constant returns slightly modifies the results of the GMMS estimator, since the elasticity of the working time rises (from 0.28 to 0.46). As to the elasticity of shiftwork, though it increases slightly (from 0.30 to 0.52), it remains statistically equivalent to that of capital.

Table 5 : Production Function with Capital Operating Time and Working Time

	OLS	***Within***	**GMMD***	**GMMS***
β_L	0.649 (0.056)	0.653 (0.071)	0.481 (0.208)	0.686 (0.122)
β_K	0.301 (0.048)	0.204 (0.065)	-0.105 (0.19)	0.344 (0.108)
β_{DHT}	0.148 (0.096)	0.283 (0.104)	0.185 (0.344)	0.275 (0.231)
β_{NOP}	0.112 (0.038)	0.135 (0.042)	0.024 (0.146)	0.301 (0.145)
$\beta_K = \beta_{NOP}$ [p-value]	9.11 [0.00]	0.76 [0.38]	0.37 [0.54]	0.05 [0.83]
Constant returns to scale				
β_L	0.685 (0.045)	0.724 (0.055)	**	0.655 (0.154)
β_K	0.315	0.276		0.345
β_{DHT}	0.155 (0.097)	0.296 (0.104)		0.459 (0.215)
β_{NOP}	0.107 (0.039)	0.129 (0.042)		0.519 (0.134)
$\beta_K = \beta_{NOP}$ [p-value]	11.45 [0.00]	4.24 [0.04]		1.06 [0.30]

Note : Year and sectoral dummies included in all models

* Corrected two-step standard errors in parentheses (Windmeijer, 2004)

** Results are not reported when the Wald test of the constant returns to scale hypothesis is not accepted in the restricted models.

Since taking hours of work into consideration leads to the counterintuitive result of output elasticities that are statistically insignificant and lower than those of labour alone—in contrast to the results in the literature (Hamermesh 1993)—we proceed to new estimations without this variable.

Estimating a Cobb-Douglas type production function with three factors (capital, labour, and shiftwork) yields results similar to the foregoing for all estimators. In the case of the GMMS estimator, we find an elasticity of shiftwork that is statistically equivalent to that of capital (Table 6). To test the robustness of this result, the estimations were performed using alternative indicators of the use of shiftwork. Again, we find equality between the output elasticity of capital and of shiftwork (Table 6).

Table 6 : Cobb-Douglas Production Function with Shiftwork

	OLS	Within	GMMD*	GMMS*	Shiftwork indicator	
					Arithmetic	Harmonic
β_L	0.64 (0.06)	0.65 (0.07)	0.48 (0.21)	0.67 (0.13)	0.67 (0.13)	0.67 (0.12)
β_K	0.30 (0.05)	0.20 (0.07)	-0.11 (0.18)	0.34 (0.11)	0.34 (0.11)	0.32 (0.10)
β_{NOP}	0.11 (0.04)	0.13 (0.04)	0.02 (0.15)	0.30 (0.14)	0.29 (0.13)	0.40 (0.22)
$\beta_K = \beta_{NOP}$ *[p-value]*	9.37 *[0.00]*	0.73 *[0.39]*	0.37 *[0.54]*	0.04 *[0.84]*	0.09 *[0.76]*	0.11 *[0.74]*
Constant returns to scale						
β_L	0.68 (0.05)	0.72 (0.06)	**	0.62 (0.14)	0.62 (0.14)	0.61 (0.10)
β_K	0.319	0.28		0.38	0.38	0.39
β_{NOP}	0.11 (0.04)	0.13 (0.04)		0.53 (0.12)	0.51 (0.11)	0.70 (0.20)
$\beta_K = \beta_{NOP}$ *[p-value]*	11.95 *[0.00]*	4.46 *[0.03]*		0.68 *[0.41]*	0.60 *[0.44]*	1.69 *[0.19]*

Note : Year and sectoral dummies included in all models

* Corrected two-step standard errors in parentheses (Windmeijer, 2004)

** Results are not reported when the Wald test of the constant returns to scale hypothesis is not accepted in the restricted models.

*** Wald Test for the null hypothesis $H_0 : \beta_K = \beta_{NOP}$, p-value in brackets.

Finally, as we show, the GMMD estimator behaves poorly in our sample due to the persistence of each factor and the measurement errors. Therefore, since the GMMS estimator is a linear combination of the two-stage least squares GMMS and level GMM estimators – the latter using all first-differenced instruments – it also means that the equations in levels are much more informative than the first-differenced equations. In this respect, a simpler GMM levels estimator will yield similar results.[24]

5.3. The contribution *of operating hours and hours of work* in the production function

The statistical contribution of operating hours and hours of work can be evaluated with the test proposed by Bond, Bowsher, and Windmeijer (2001), which compares the value of the function to be minimized to obtain the GMMS estimator under the null hypothesis $\left(\hat{\beta}_2^C\right)$ and under the alternative hypothesis $\left(\hat{\beta}_2\right)$.

Under the null hypothesis, and for *r* constraints of the type $r(\beta)=0$, the computed statistic (D_{RU}), which follows a Chi-squared distribution with *r* degrees of freedom, is given by

$$D_{RU} = N\left(J\left(\hat{\beta}_2^C\right) - J\left(\hat{\beta}_2\right)\right)$$

with $J(\beta) = \left[\frac{1}{N}\sum_{i=1}^{i=N} Z_i'\left(y_i - m\left(X_i,\beta\right)\right)\right]' W_N^{-1}\left[\frac{1}{N}\sum_{i=1}^{i=N} Z_i'\left(y_i - m\left(X_i,\beta\right)\right)\right]$.

The results (Table 6) confirm that the measure of the *hours* of work we use does not contribute any information statistically, since we accept the null hypothesis (H_0) $\beta_{DHT} = 0$, unlike in the case of the intensity of the use of shiftwork, for which we reject the null hypothesis $\beta_{NOP} = 0$.

24 We estimate the models using a GMM levels estimator. Results are close to the GMMS estimators and thus our conclusions remain valid. Results are not reported here but are available on request.

Table 7 : Contribution of Operating Hours and Working Time in the Production Function

	Stat	p-value
Working Time		
Four factors (K, L, NOP, DHT) vs. Three factors (K,L,NOP) H0 : $\beta_{DHT} = 0$	0.58	0.447
Synthetic Shiftwork Indicator		
Four factors (K,L,NOP) vs. Three factors (K,L) H0 : $\beta_{NOP} = 0$	4.39	0.036

Note: "Stat" indicates the statistic developed by Bond, Bowsher, and Windmeijer (2001). It follows a Chi-squared distribution with one degree of freedom under the null hypothesis of no contribution of the hours of work or shiftwork. Estimates are obtained by GMMS.

5.4. Comparison with previous studies

A comparison of Table 1 with our results reveals that considering shiftwork substantially improves estimates of factors' share in the economy. The corresponding coefficients are, for the most part, significant and allow estimation of marginal productivities of capital and labour that are more significant and more consistent with these factors' compensation in the value added. The assumption of constant returns to scale with respect to stocks of capital and labour cannot be rejected.

In particular, studies using French data tend to underestimate the share of capital in the economy and to overestimate the share of labour in value added, especially when firm-level data are not considered. A further debate surrounding the estimation of production functions pertains to the relative productivity of the workforce and working time. The values of these parameters come into play in discussions of potential productivity gains associated with changes to the length of the workweek. They can also be used to evaluate the feasibility of a firm's practice of perennially drawing on overtime. Empirical results are strongly divided on this matter. Various studies (Feldstein (1967) on British data, or Craine (1973) on U.S. data) obtain output elasticities with respect to individual hours of work that exceed unity. Others have found less dramatic results, either because they differentiate between behaviours according to the sector of the economy (Leslie and Wise (1980) for the United Kingdom), or because they introduce cyclical indicators or incorporate the productive services of capital (Hart and McGregor 1988, Anxo and Bigsten1989). Under these conditions, our results show that omitting the capital operating time may introduce a bias into the results. Indeed, for a given shiftwork organization, increasing the hours worked leads to a rise in the capital operating time, which will allow an increase in production. If this effect is not considered, the output elasticity of working time may be overestimated. Anxo and Bigsten (1989), lacking a measure of the capital operating time, propose estimating a production function for Swedish industry that integrates capital, the workforce, the working time, and a capacity utilization rate. They observe a negative output elasticity of the capacity utilization rate. This paradoxical result—since they retained this indicator a priori as a business cycle measure of the gap between the supply of, and demand for, goods—could be explained if the most productive equipment is used first, and the remainder only brought into service to deal with substantial recoveries in economic activity. This could be attributable to the existence of several generations of equipment or, more generally, by heterogeneity of capital. In this event, we would be observing a “saturation effect,” explained by Cette et al. (1991), as full production capacity is approached. Since we have data on the capital operating time, we obtain, following Hart and McGregor (1988), identical output elasticities of capital and its operating hours.

6. Robustness Analysis

In this section, we discuss the specification of the production function. We consider a flexible translog production function and analyze to what extent our results are driven by the Cobb-Douglas formulation of the production mix. The Translog specification is retained since it can be considered as a second order approximation of any twice differentiable technology (Fuss, McFadden, and Mundlack, 1978; Chambers, 1988) and the Cobb-Douglas production function is a restricted case of the Translog specification. The results in this section are discussed in details in Heyer, Pelgrin, and Sylvain (2004).

6.1. Estimation of a Translog production function

We consider the following relation (Christensen, Jorgenson, and Lau, 1971):

$$\ln\left(y_{i,t}\right)=\sum_{j=1}^{j=4}\beta_i \ln\left(x_{it}^j\right)+\frac{1}{2}\sum_{j=1}^{j=4}\sum_{k=1}^{k=4}\beta_{jk}\ln\left(x_{it}^j\right)\ln\left(x_{it}^k\right)+\mu_t+\delta_s+(\eta_i+v_{i,t}+m_{i,t}) \qquad (12)$$

where $x^1 = L$ represents the workforce, $x^2 = K$, the stock of capital, $x^3 = DUE$ the capital operating time, $x^4 = DHT$ the working time, μ_t a time effect capturing an exogenous Hicksian technical progress, and δ_s is an individual sectoral effect.

We also assume that

$$\begin{aligned} v_{i,t} &= \rho \times v_{i,t-1} + e_{i,t} \\ e_{i,t}, m_{i,t} &\sim MA(0). \end{aligned} \qquad (13)$$

Incorporating an autoregressive error term into the global error term thus yields a dynamic relation. Finally, in order to avoid multicolinearity from the cross-terms, we assume that the logarithms of the factors are centered (Aiken and West, 1991). Therefore, from equations (12) and (13), we can write:

$$\begin{aligned} \ln\left(y_{i,t}\right) &= \rho \ln\left(y_{i,t-1}\right)+\sum_{i=1}^{i=4}\tilde{\beta}_i\left(\tilde{x}_{it}^j-\rho\tilde{x}_{i,t-1}^j\right) \\ &+\frac{1}{2}\sum_{j=1}^{j=4}\sum_{k=1}^{k=4}\tilde{\beta}_{kj}\left(\tilde{x}_{it}^j\tilde{x}_{it}^k-\rho\tilde{x}_{i,t-1}^j\tilde{x}_{i,t-1}^k\right) \\ &+(\gamma_t-\rho\gamma_{t-1})+\delta_s\left(1-\rho\right)+(\eta_i(1-\rho) \\ &+e_{it}+m_{it}-\rho m_{i,t-1}) \end{aligned} \qquad (14)$$

with $\tilde{x}_{it}^j=\ln\left(x_{it}^j\right)-\overline{x}^j$, $\overline{x}=\frac{1}{nobs}\sum_i\sum_t\ln\left(x_{it}\right)$, and $nobs=\sum_{i=1}^{i=N}t_i$;

where t_i, is the number of successive years of presence of the firm i in the sample.

In order to estimate (14), we need to take into account two limitations of the Translog specification (Diewert, 1971). First, this representation is only valid at the unknown approximation point or its neighborhood. Generally, the median or average point is used in empirical studies. Following Biscourp et al. (2003) and Chambers (1988), we report here the distribution of the different elasticities (output and substitution elasticities) as well as the median estimates. Second, while Cobb-Douglas or CES production functions satisfy regularity conditions (positive marginal productivities, decreasing returns to scale for each factor, convexity of the isoquants, and positive owned-elasticities), this might not be the case for the Translog specification. There is a trade-off between the flexibility of the functional form and the respect of the validity conditions. Therefore, we impose, when necessary, these conditions and follow the approaches developed by Lau (1978), Gallant and Golub (1984) and Ryan and Wales (2000).

Results are presented in Tables 8a and 8b.[25] They show that the median output elasticities of factors are close to the coefficients of the Cobb-Douglas production function, except for the elasticity of the shiftwork variable, 0.19, which is less than the capital elasticity, 0.30, and the elasticity of the working time which is largely inferior to the output elasticity of labour. At the same time, the partial elasticities of substitution provide evidence that pairwise production's factors are substitutable: ceteris paribus, an increase of a factor's price leads to a decrease of this factor in the input mix and thus an increase of other factors. This confirms that the development of shiftwork is a credible alternative to investment. Moreover, if we assume that the adjustment of shiftwork is more immediate than the adjustment of capital, then shiftwork will allow more flexibility in the production process during unexpected changes of factors cost. Nevertheless, as we point out in Section 5, the substitutability of the couple (labour, working time) should be interpreted with caution due to the imprecision and the measurement issues of the hours of work.

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[25] Results for the GMMS estimator are reported in Table 8. Estimates are presented in Appendix A2.6. Other results are available on request.

Table 8a : Distribution of *Output* Elasticities – 4-factors Translog Production Function.

	L	K	NOP	DH
95%	0.75	0.42	0.28	0.35
75%	0.67	0.36	0.23	0.30
50%	0.62	0.30	0.19	0.25
25%	0.57	0.26	0.14	0.19
5%	0.50	0.21	0.10	0.13

Table 8b : Distribution of Partial Elasticities of Substitution

	K,L	L,NOP	L,DHT	K,NOP	K,DHT	N,DHT
95%	3.4	0.8	0.2	3.7	1.6	1.1
75%	2.8	0.7	0.1	2.6	1.4	1.0
50%	2.6	0.5	0.0	2.1	1.3	0.9
25%	2.5	0.2	**-0.1**	1.9	1.2	0.9
5%	2.3	**-0.7**	**-0.4**	1.6	1.1	0.8

Note : Under the regularity conditions, 945 observations are available.

As previously, we proceed to new estimations without the hours of work. Results show that the working time does not affect our results – elasticities and qualitative interpretations are the same. Note, however, that the dynamic representation is now accepted while it was statistically rejected with the four-factor specification.[26]

6.2. Cobb-Douglas or Translog?

Since the Cobb-Douglas production function can be seen as a constrained version of the Translog specification, we test to what extent our results are robust to the functional form by using the methodology proposed by Bond, Bowsher, and Windmeijer (2001).[27] Specifically, we compare the constrained two-step GMMS estimator (Cobb-Douglas technology) and the unconstrained one (Translog technology). Results reported in Table 10 show that the null hypothesis of a Cobb-Douglas production function is not rejected at standard significance level, e.g. the factors of production are substitutable and elasticities of substitution are unitary. Interestingly, the Cobb-Douglas formulation is ruled out if durations of factor utilization are not taken into consideration in the specification: the p-values are less than 0.01 in both cases – the

[26] Results are not reported here but are available on request.

unconstrained and the constrained estimations. The same result emerges when considering a static representation of the production function. Except when we impose the regularity condition for the three-factor model, the null hypothesis of a Cobb-Douglas production function is not accepted at standard levels. Therefore, our empirical evidence suggest that a Cobb-Douglas production function is a correct functional form of the technology in our sample, especially when studying the contribution of durations of factor utilization.

Table 9: Translog versus Cobb-Douglas production function

		Unconstrained Estimation	Regularity Conditions
Dynamic Representation:			
Four factors (K,L, NOP, DHT)	Stat	14.40	12.90
	p-value	0.16	0.23
Three factors (K,L, NOP)	Stat	6.40	5.10
	p-value	0.38	0.53
Two factors (K,L)	Stat	17.70	15.90
	p-value	< 0.01	< 0.01
Static Representation:			
Three factors (K,L,NOP)	Stat	12.00	8.50
	p-value	0.06	0.20
Two factors (K,L)	Stat	14.00	13.40
	p-value	< 0.01	< 0.01

Note: The degrees of freedom of the Chi-Squared is 10, 6 and 3, respectively, for the four-, three-, and two-factor models.

7. Conclusion

Our analysis shows that shiftwork has a significant impact on wealth creation, and the output elasticity of is equivalent to that of capital. All else being equal, and assuming a homogeneous capital stock, there is full equivalence between increasing the capital stock or developing shiftwork. Moreover, these results are obtained using an estimation method (the GMMS) that appears more efficient than traditional methods (OLS, Within, and the GMMD), which bolsters our conclusion. At the same time, GMMD estimations suggest that the results obtained depend essentially on account being taken of the equations in levels, and thus of the instruments in first differences. Conversely, we are unable to identify a truly significant impact of working time,

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[27] See Section 5.3.

probably because of measurement errors on that variable and its limited variance. In addition, we show that our results are robust to the choice of the functional form. Interestingly, the Cobb-Douglas production function is the true technology if we take into account factor utilization whereas the Translog production function matters if labour and capital are the unique inputs.

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Appendix 1: Data used and construction of the variables

A1.1 Shiftwork and Capital Operating Time

Shiftwork is a way of working in relays in which several teams succeed one another in time, with overlap either nonexistent or limited to conveying information on the status of the work. Traditionally, we distinguish between:

- **discontinuous** work (2X8), which permits extended operation during the day, but retains nights and weekends as downtime;
- **semi-continuous** work (3x8), which permits work to be uninterrupted except on weekends;
- **continuous** work, organized without any stops at all, generally with 4 or 5 teams (4x8 or 5x8).

Thus, all else being equal, the more extensive the use of shifts, the longer the capital operating time will be. The operating time for a given piece of equipment will be doubled when two successive teams use it (compared to the situation without alternation), tripled when there are three teams, and so on.

Measures of the capital operating time (DUE) are based on the shiftwork patterns and the hours of work. They usually correspond to the product of a synthetic shiftwork indicator (NOP) times the average working time (DHT):

$$DUE = NOP \times DHT\ .$$

A1.2 Construction of the variables

The **value added at factor cost** at current price (VACF_VAL) is computed using data from the Balance-Sheet Data Office with the following relationship:

VACF_VAL = FL + FM + FN – (FS + FT + FU + FV + FW) + FO – FX,

where FL is net sales; FM, stored production; FN, capitalized production; FS, purchases of goods; FT, variation in the stock of goods; FU, purchases of commodities and other supplies; FV, variation in the stock of commodities and other supplies; FW, other purchases and external expenses; FO, operating subsidies; FX, sales and income taxes and related payments.

The real value added (Y) is then obtained by deflating with a sectoral price index (level *naf36*).

Owing to the absence of information on the equipment's efficiency over time, the ***real stock of capital (K)*** computed at the firm level is a gross stock of capital. Because of the nature of the available data, this is close to the entirety of all tangible assets. It is calculated using the following relationship:

$$K_t = I_t + (1-\delta) K_{t-1}$$

where δ represents the constant rate of depreciation, fixed at 5 per cent (Sylvain 2003a).

The initial volume of capital is computed under the assumption that it was all acquired on the initial date, with an adjustment for its age at that date. The age of capital is determined from the share of amortized capital, assuming that the amortization is linear. The time series of investments and the initial stock of capital are deflated by sectoral price indexes for investment (level NAF*36*).

The ***total workforce (L)*** and the ***working time (DHT)*** are taken from the annual survey of capital operating time.

The ***synthetic shiftwork indicator (NOP)*** is computed from information on the shiftwork patterns supplied by the annual survey of capital operating time. For each firm, this indicator is defined such that:

$$NOP = \frac{\sum_n n \times \alpha_n \times p_{it}^n}{\sum_n \alpha_n \times p_{it}^n},$$

where n is the number of teams; p_i^n, the proportion of the workforce working in n teams; and α_n, constant coefficients.

Given the available data, we assume that discontinuous, semi-continuous, and continuous work correspond to two, three, and five teams.

The retained coefficients α_n yield the usual measures for the intensity of the use of shiftwork (Table A). The harmonic approach defines the intensity of the use of shiftwork as the harmonic mean of the number of teams, and the arithmetic approach as the arithmetic mean of the number of teams. The econometric indicator used in this study retains the coefficients α_n generated by econometric estimations on individual data (Sylvain, 2003b).

Table A : Shiftwork Indicators

	Econometric Approach *	Harmonic Approach	Arithmetic Approach
α_1	1	1	1
α_2	0.95	0.50	1
α_3	0.91	0.33	1
α_5	0.86	0.20	1

Source : Sylvain (2003b)

Appendix 2 : Results of Estimations

A2.1 : Standard Cobb-Douglas Production Function with Capital and Labour

	Ols[2]	Within[2]	GMMD[2] (t-2/t-4)	GMMD[2] (t-3/t-5)	GMMS[2] (t-2/t-4)	GMMS[2] (t-3/t-5)
y_{t-1}	0.912	0.513	0.039	0.118	0.787	0.875
	(0.018)	(0.044)	(0.11)	(0.12)	(0.078)	(0.073)
l_t	0.595	0.653	0.475	0.412	0.666	0.369
	(0.066)	(0.069)	(0.181	(0.23	(0.193	(0.133
l_{t-1}	-0.531	-0.284	0.151	-0.005	-0.409	-0.277
	(0.065)	(0.079)	(0.210)	(0.185)	(0.179)	(0.147)
k_t	0.202	0.235	-0.069	-0.128	0.374	0.296
	(0.072)	(0.068)	(0.219)	(0.209)	(0.300)	(0.186)
k_{t-1}	-0.176	-0.201	-0.098	0.094	-0.398	-0.263
	(0.071)	(0.078)	(0.240)	(0.183)	(0.286)	(0.171)
m1[1]	-1.40	3.33	-1.13	-1.64	-5.70	-5.46
p-value	(0.161)	(0.001)	(0.261)	(0101)	(0.00)	(0.00)
m2[1]	-0.77	-0.12	-1.16	-0.9	-0.76	-0.55
p-value	(0.442)	(0.907)	(0.248)	(0.370)	(0.448)	(0.584)
Comfac[1]	5.53	1.85	0.74	0.29	4.68	1.15
p-value	(0.063)	(0.396)	(0.692)	(0.866)	(0.096)	(0.563)
Sargan[1]			72.24	64.96	111.28	85.17
p-value			(0.601)	(0.738)	(0.271)	(0.855)
Dsar[1]					39.04	20.21
p-value					(0.063)	(0.822)
Dynamic Representation						
ρ	0.907	0.518	0.03	0.126	0.768	0.878
	(0.017)	(0.044)	(0.105)	(0.120)	(0.062)	(0.069)
β_L	0.65	0.658	0.48	0.436	0.884	0.466
	(0.057)	(0.071)	(0.169)	(0.221)	(0.137)	(0.152)
β_K	0.307	0.203	-0.084	-0.111	0.171	0.422
	(0.048)	(0.065)	(0.149)	(0.196)	(0.164)	(0.163)
Crs[1]	0.94	2.99	11.71	6.43	0.2	0.53
p-value	(0.331)	(0.084)	(0.001)	(0.011)	(0.655)	(0.466)
Constrained Estimation $\beta_L + \beta_K = 1$						
ρ	0.901	0.508	0.105	0.069	0.602	0.649
	(0.016)	(0.043)	(0.105)	(0.113)	(0.129)	(0.121)
β_L	0.679	0.726	0.859	0.89	0.843	0.72
	(0.046)	(0.056)	(0.155)	(0.164)	(0.134)	(0.126)

Notes:

1. m1 and m2 are tests for the first- and second-order serial correlation, asymptotically N(0,1). Sargan and Dsar are the statistics for the overidentification tests. Comfac is a minimum distance test of the non-linear common factor restrictions imposed in the restricted models. Crs is a Wald test of the constant returns to scale hypothesis under the restricted model.
2. Asymptotic standard errors in parentheses for OLS and Within, and corrected two-step standard errors for GMMD and GMMS. Year and sectoral dummies included in all models.

A2.2 : Cobb-Douglas Production Function with Capital Operating Time and Working Time

	Ols	Within	GMMD (t-2/t-4)	GMMD (t-3/t-5)	GMMS (t-2/t-4)	GMMS (t-3/t-5)
y_{t-1}	0.909	0.5	0.033	0.126	0.784	0.759
	(0.017)	(0.044)	(0.091)	(0.117)	(0.068)	(0.083)
l_t	0.59	0.648	0.498	0.495	0.644	0.569
	(0.066)	(0.069)	(0.178)	(0.217)	(0.15)	(0.147)
l_{t-1}	-0.522	-0.274	0.086	-0.025	-0.415	-0.379
	(0.066)	(0.077)	(0.203)	(0.193)	(0.142)	(0.145)
k_t	0.191	0.228	-0.103	-0.098	0.373	0.316
	(0.072)	(0.066)	(0.223)	(0.199)	(0.242)	(0.201)
k_{t-1}	-0.167	-0.183	-0.089	0.062	-0.381	-0.239
	(0.07)	(0.078)	(0.235)	(0.187)	(0.229)	(0.183)
dht_t	0.184	0.362	0.606	0.272	0.507	0.413
	(0.113)	(0.114)	(0.275)	(0.333)	(0.389)	(0.307)
dht_{t-1}	-0.084	0.085	0.3	0.256	-0.572	0.034
	(0.093)	(0.104)	(0.363)	(0.294)	(0.348)	(0.357)
nop_t	0.116	0.139	-0.018	0.025	0.196	0.305
	(0.038)	(0.045)	(0.137)	(0.139)	(0.112)	(0.13)
nop_{t-1}	-0.095	-0.059	0.007	-0.185	-0.051	-0.279
	(0.036)	(0.046)	(0.093)	(0.124)	(0.081)	(0.133)
m1	-1.37	3.43	-1.25	-1.87	-5.82	-5.13
p-value	(0.172)	(0.001)	(0.212)	(0.062)	0	0
m2	-0.64	-0.08	-1.71	-1.27	-0.78	-0.45
p-value	(0.522)	(0.935)	(0.087)	(0.203)	(0.438)	(0.651)
Comfac	7.27	7.27	1.24	3.01	4.87	2.14
p-value	(0.122)	(0.123)	(0.871)	(0.556)	(0.301)	(0.71)
Sargan			97.54	85.01	149.71	124.4
p-value			(0.523)	(0.759)	(0.183)	(0.646)
Dsar					52.17	39.39
p-value					(0.04)	(0.321)
Dynamic Representation						
ρ	0.904	0.503	0.031	0.083	0.777	0.768
	(0.017)	(0.043)	(0.082)	(0.114)	(0.071)	(0.073)
β_L	0.649	0.653	0.463	0.481	0.826	0.686
	(0.056)	(0.071)	(0.171)	(0.208)	(0.102)	(0.122)
β_K	0.301	0.204	-0.115	-0.105	0.158	0.344
	(0.048)	(0.065)	(0.151)	(0.19)	(0.112)	(0.108)
β_{DHT}	0.148	0.283	0.53	0.185	0.493	0.275
	(0.096)	(0.104)	(0.291)	(0.344)	(0.277)	(0.231)
β_{NOP}	0.112	0.135	0.003	0.024	0.052	0.301
	(0.038)	(0.042)	(0.123)	(0.146)	(0.091)	(0.145)
Crs	1.33	3.24	11.08	5.67	0.02	0.11
p-value	(0.249)	(0.072)	(0.001)	(0.017)	(0.894)	(0.735)
$\beta_K = \beta_{NOP}$	9.11	0.756	0.49	0.37	0.55	0.05
p-value	(0.00)	(0.384)	(0.49)	(0.54)	(0.46)	(0.83)

Table A2.2 (Con't): Cobb-Douglas Production Function with Capital Operating Time and Working Time

Constrained Estimation $\beta_L + \beta_K = 1$						
	Ols	**Within**	**GMMD (t-2/t-4)**	**GMMD (t-3/t-5)**	**GMMS (t-2/t-4)**	**GMMS (t-3/t-5)**
ρ	0.898	0.493	0.097	0.062	0.594	0.538
	(0.016)	(0.042)	(0.084)	(0.114)	(0.122)	(0.118)
β_L	0.685	0.724	0.817	0.901	0.833	0.655
	(0.045)	(0.055)	(0.137)	(0.159)	(0.098)	(0.154)
β_{DHT}	0.155	0.296	0.616	0.298	0.619	0.459
	(0.097)	(0.104)	(0.3)	(0.357)	(0.304)	(0.215)
β_{NOP}	0.107	0.129	0.015	0.097	0.206	0.519
	(0.039)	(0.042)	(0.129)	(0.155)	(0.086)	(0.134)
$\beta_K = \beta_{NOP}$	11.45	4.24	0.94	0.00	0.15	1.06
p-value	(0.00)	(0.04)	(0.33)	(0.99)	(0.70)	(0.30)

Note: See Table A2.1

A2.3 : Cobb-Douglas Production Function with Shiftwork

	Ols	**Within**	**GMMD (t-2/t-4)**	**GMMD (t-3/t-5)**	**GMMS (t-2/t-4)**	**GMMS (t-3/t-5)**
y_{t-1}	0.909	0.509	0.03	0.135	0.786	0.787
	(0.018)	(0.043)	(0.091)	(0.113)	(0.068)	(0.073)
l_t	0.585	0.64	0.518	0.483	0.654	0.568
	(0.066)	(0.069)	(0.181)	(0.221)	(0.155)	(0.154)
l_{t-1}	-0.518	-0.272	0.094	-0.027	-0.43	-0.41
	(0.066)	(0.078)	(0.198)	(0.189)	(0.155)	(0.149)
k_t	0.2	0.236	-0.102	-0.136	0.367	0.334
	(0.071)	(0.067)	(0.196)	(0.198)	(0.236)	(0.201)
k_{t-1}	-0.176	-0.208	-0.086	0.104	-0.381	-0.264
	(0.07)	(0.078)	(0.227)	(0.18)	(0.22)	(0.183)
nop_t	0.114	0.137	0.022	0.015	0.221	0.296
	(0.039)	(0.047)	(0.123)	(0.138)	(0.112)	(0.126)
nop_{t-1}	-0.097	-0.065	0.018	-0.19	-0.059	-0.297
	(0.037)	(0.046)	(0.092)	(0.123)	(0.086)	(0.118)
m1	-1.34	3.44	-1.17	-1.94	-5.63	-5.32
p-value	(0.181)	(0.001)	(0.240)	(0.052)	(0.00)	(0.00)
m2	-0.54	0.16	-1.15	-1.01	-0.5	-0.27
p-value	(0.591)	(0.876)	(0.249)	(0.312)	(0.615)	(0.785)
Comfac	5.74	2.19	0.58	2.75	4.52	1.6
p-value	(0.125)	(0.535)	(0.9)	(0.433)	(0.211)	(0.659)
Sargan			99.14	85.92	156.17	124.3
p-value			(0.534)	(0.782)	(0.126)	(0.693)
Dsar					57.03	38.37
p-value					(0.014)	(0.362)
Dynamic Representation						
ρ	0.905	0.513	0.034	0.09	0.788	0.774
	(0.017)	(0.043)	(0.083)	(0.110)	(0.062)	(0.071)
β_L	0.644	0.646	0.509	0.482	0.836	0.674
	(0.056)	(0.071)	(0.176)	(0.212)	(0.104)	(0.125)
β_K	0.303	0.202	-0.11	-0.113	0.143	0.338
	(0.048)	(0.065)	(0.147)	(0.183)	(0.116)	(0.11)
β_{NOP}	0.111	0.133	0.031	0.017	0.053	0.299
	(0.038)	(0.042)	(0.113)	(0.146)	(0.091)	(0.138)
Crs	1.5	3.69	9.58	5.99	0.03	0.02
p-value	(0.220)	(0.055)	(0.002)	(0.014)	(0.866)	(0.896)
	9.37	0.73	0.72	0.37	0.36	0.04
p-value	(0.000)	(0.390)	(0.400)	(0.540)	(0.550)	(0.840)
Constrained Estimation $\beta_L + \beta_K = 1$						
ρ	0.898	0.504	0.085	0.062	0.578	0.534
	(0.016)	(0.042)	(0.09)	(0.113)	(0.114)	(0.132)
β_L	0.681	0.721	0.846	0.921	0.82	0.616
	(0.045)	(0.056)	(0.141)	(0.155)	(0.1)	(0.141)
β_{NOP}	0.106	0.127	0.046	0.089	0.231	0.523
	(0.039)	(0.043)	(0.121)	(0.161)	(0.092)	(0.119)
$\beta_K = \beta_{NOP}$	11.95	4.46	0.40	0.00	0.22	0.68
p-value	(0.00)	(0.030)	(0.530)	(0.970)	(0.640)	(0.410)

A2.4 : Cobb-Douglas Production Function with Alternative Shiftwork indicators (GMMS estimates)

	Arithmetic Approach	**Harmonic Approach**
y_{t-1}	0.788 (0.072)	0.789 (0.078)
l_t	0.56 (0.154)	0.551 (0.149)
l_{t-1}	-0.403 (0.15)	-0.387 (0.155)
k_t	0.334 (0.2)	0.296 (0.2)
k_{t-1}	-0.263 (0.184)	-0.236 (0.185)
nop_t	0.285 (0.119)	0.345 (0.207)
nop_{t-1}	-0.289 (0.112)	-0.35 (0.177)
m1 p-value	-5.32 (0..00)	-5.23 (0.00)
m2 p-value	-0.27 (0.787)	-0.32 (0.747)
Comfac p-value	1.7 (0.637)	2.01 (0.57)
Sargan p-value	124.49 (0.689)	119.95 (0.784)
Dsar p-value	38.28 (0.366)	36.69 (0.437)
Dynamic Representation		
ρ	0.774 (0.071)	0.778 (0.07)
β_L	0.671 (0.127)	0.672 (0.116)
β_K	0.343 (0.111)	0.319 (0.103)
β_{NOP}	0.288 (0.131)	0.397 (0.222)
Crs p-value	0.02 (0.880)	0.01 (0.922)
$\beta_K = \beta_{NOP}$ p-value	0.09 (0.760)	0.11 (0.740)
Constrained Estimation $\beta_L + \beta_K = 1$		
ρ	0.537 (0.128)	0.542 (0.123)
β_L	0.618 (0.135)	0.611 (0.100)
β_{NOP}	0.507 (0.112)	0.7 (0.204)
$\beta_K = \beta_{NOP}$ p-value	0.60 (0.44)	1.69 (0.19)

A2.5 Four-factors Translog Production Function - GMMS Estimates

	Unconstrained Estimation	Regularity Conditions
ρ	0.701	0.694
	(0.058)	(0.078)
β_L	0.612	0.623
	(0.084)	(0.089)
β_K	0.315	0.307
	(0.054)	(0.053)
β_N	0.139	0.187
	(0.074)	(0.077)
β_D	0.16	0.244
	(0.168)	(0.188)
β_{LL}	0.128	0.062
	(0.083)	(0.092)
β_{KK}	0.073	0.033
	(0.053)	(0.060)
β_{NN}	0.111	0.005
	(0.117)	(0.102)
β_{DD}	-0.132	-0.160
	(1.125)	(1.207)
β_{KL}	-0.218	-0.121
	(0.125)	(0.139)
β_{KN}	-0.113	-0.026
	(0.074)	(0.072)
β_{LN}	0.198	0.083
	(0.106)	(0.100)
β_{LD}	0.488	0.122
	(0.307)	(0.333)
β_{KD}	-0.288	-0.063
	(0.202)	(0.207)
β_{ND}	0.144	-0.036
	(0.531)	(0.594)

Note: Corrected two-step standard errors. Year and sectoral dummies included in all models.

A2.6 Three-factors Translog Production Function

	Unconstrained Estimation	Regularity Conditions
ρ	0.698	0.697
	(0.061)	(0.075)
β_L	0.601	0.607
	(0.081)	(0.092)
β_K	0.326	0.314
	(0.050)	(0.053)
β_N	0.132	0.196
	(0.075)	(0.076)
β_{LL}	0.117	0.06
	(0.078)	(0.085)
β_{KK}	0.074	0.035
	(0.050)	(0.056)
β_{NN}	0.116	-0.011
	(0.112)	(0.103)
β_{KL}	-0.221	-0.126
	(0.116)	(0.125)
β_{KN}	-0.117	-0.024
	(0.077)	(0.08)
β_{LN}	0.207	0.08
	(0.107)	(0.105)

Note: Corrected two-step standard errors. Year and sectoral dummies included in all models.