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INFLUENCE THE SIZE OF THE OKUN’S LAW COEFFICIENT?”**

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# “How do technical change and technological distance influence the size of the Okun’s Law coefficient?”

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## Abstract

How does technical change influence the size of the Okun’s Law coefficient? Using a nonlinear version of Okun’s Law augmented with technical change and technological distance, we show that the impact of output movements on unemployment variations is influenced by the imitation or innovation origins of technical change.

**Key words:** Okun’s Law, Technological frontier, Technical change, Nonlinear model.

## Introduction

In the early 1960s Arthur Okun observed a negative empirical correlation between output and unemployment in the short run with postwar data series (Okun, 1962). Since that time, a number of papers have examined various aspects of the empirical properties of the Okun’s Law (OL hereafter) such as its magnitude (Moosa 1997, Freeman 2001), the stability of the unemployment-GDP

correlation (Weber 1995, Lee 2000, Tavera and Perman 2005), and the asymmetric and nonlinear characteristics of the GDP-unemployment linkage (Crespo-Cuaresma 2003, Silvapulle et al. 2004, Harris and Silverstone 2001, Knotek 2007).

While these papers try to make the dynamic characteristics of the OL more precise, they systematically maintain the assumption that the output-unemployment correlation coefficient, or Okun's Law Coefficient (OLC hereafter), can be considered as a reduced-form, or semi-reduced form, parameter which incorporates several fundamental structural parameters such as those from the firms' optimal demand for labour, the macroeconomic production function, the labour force participation equation, or the adjustment mechanisms at work in the labour market.

While this approach has the undeniable advantages of maintaining the analysis in the spirit of the initial OL estimates and authorizing comparisons with previous estimations, it can hide the underlying mechanisms which are at work between output and unemployment movements. Some papers have tried to go deeper into the underlying mechanisms of the net impact of short-run GDP movements on unemployment rate variations by searching for factors influencing the size of the estimated OLC across countries. For instance, IMF (2010) tries to explain the variation in the estimated values of the OLC across countries by key labor market institutions, such as employment protection legislation, policies such as unemployment benefits or the share of temporary workers. Ball, Leigh and Loungani (2012) try to estimate the relationship between the estimated OLC for 20 OECD countries and the average unemployment rate, the OECD overall Employment Protection Legislation Index, the share of youth unemployment in total unemployment and the share of long-term unemployment in total unemployment. Similarly, Herwartz and Niebuhr (2011) investigate the influence of national labor market institutions and regional characteristics on OLC disparities across European regions.

However, an important limitation of these papers comes from the fact that they systematically use a two-step econometric methodology consisting of the estimation of the OLC for several countries in the first step, and the regression of the estimated OLCs on selected indicators in the second step. While

this methodology has the advantage of simplicity, it implicitly assumes that the estimated OLC converges towards the true OLC in the first step.

This paper is in the vein of this group of empirical analyses since it also tries to go deeper into the empirical characteristics of the Okun's Law relationship by evaluating the influence of both technical change and the technological gap on the sensitivity of unemployment variations to real GDP movements. Our research is thus directly related to recent papers which show that, contrary to conventional Okun's Law philosophy, unemployment variations may be related to the permanent component of real GDP (Sinclair 2009) and that technology absorption can distort the relationship between output growth and unemployment (Hoon and Ho 2007, Vandebussche, Aghion and Meghir 2006, Duernecker 2008). Moreover, evaluating the particular impact of the technical change component of output movements on unemployment can highlight some of the theoretical foundations of the Okun's Law relationship which is usually considered as a purely empirical regularity.

While following recent contributions that seek to reveal underlying mechanisms relating unemployment rate variations to short-run GDP movements, our empirical strategy avoids the two-step limitation mentioned above. We propose a model in which cross-country differences in the pace of technical change and the rate of technology adoption can account for a part of the observed divergence of the Okun's Law coefficient across economies. A non-parametric Malmquist approach (Caves, Christensen and Diewert, 1982) is first used to decompose technical change into two separate elements: the movement of the world technological frontier and the variation of the technological distance between a given country and the world technological frontier. The first component is a measure of technical change in the most efficient country (the leader country) and the second component constitutes an estimate of technological absorption capacity of follower countries. Two alternative non-linear augmented versions of the Okun's Law including the two components are then estimated to evaluate their relative influence on the correlation between unemployment and GDP variations. Empirical results show that the absolute value of the unemployment GDP correlation is negatively related to the rate of technical change and positively related to the size of the technological

gap. Moreover, the mean combined effect of technical change and technological gap accounts for nearly 30% of the total Okun's Law coefficient.

The rest of the paper proceeds as follows. Section 2 outlines the underlying theoretical model and explains how the non-linear effects of technical change and technological gap emerge. Section 3 presents econometric methods. Section 4 reports data sources and presents and discusses empirical results. Section 5 concludes the paper. Appendix 1 reports Chow test statistics for breaks in the basic OL relationship, and Appendix 2 reports the sequence of squared errors for threshold tests.

## 2. Theoretical background

In the spirit of the decomposition suggested by Prachowny (1993), we assume that a simple decomposition of real output into its main component can be obtained with the following traditional Cobb-Douglas version of the production function (including disembodied technology):

$$Y = AN^\alpha K^\beta = A[P \cdot (1 - u)]^\alpha (C \cdot K)^\beta \quad (1)$$

with  $Y$  being real output,  $N$  the number of workers,  $K$  the capital input,  $C$  the capacity utilization rate,  $A$  being Total Factor Productivity (TFP),  $P$  the labor force, and  $u$  the unemployment rate.

The potential output level is obtained when TFP and employment equal their respective long run equilibrium levels and when the capacity utilization rate is 1. In the case of employment, we assume that full employment is a situation where the labor force is at its long run equilibrium level while the unemployment rate equals its long run equilibrium level (that is, the natural rate of unemployment).

$$\bar{Y} = \bar{A}\bar{N}^\alpha \bar{K}^\beta = \bar{A}[\bar{P} \cdot (1 - \bar{u})]^\alpha \bar{K}^\beta \quad (2)$$

where potential and/or long-run equilibrium levels of the variables are denoted by bars.

Calculating the ratio of real output to potential output and taking logs of the resulting equation allows the unemployment gap to be expressed as

$$(u - \bar{u}) = -(1/\alpha) \cdot yg + (1/\alpha) \cdot ag + pg + (\beta/\alpha) \cdot c \quad (3)$$

where  $yg = \ln(Y/\bar{Y})$  denotes the log of the real output gap,  $ag = \ln(A/\bar{A})$  is the log of the TFP gap,  $pg = \ln(P/\bar{P})$  is the log of the labor force participation gap,  $c = \ln(C)$  is the log of the capacity utilization rate (note that  $\bar{c} = 1$ ), and  $u$  is approximately equal to  $-\ln(1 - u)$ .

We then adopt the following assumptions to characterize the movements of the labor force participation gap, the TFP gap and the capacity utilization rate. First, as labor force participation and capacity utilization are pro-cyclical, rising during expansions and falling during recessions, these variables are modeled as follows:

$$pg = f(yg) \text{ with } f'(yg) > 0 \quad (4)$$

$$c = g(yg) \text{ with } g'(yg) > 0 \quad (5)$$

While the mechanism at work is standard in the case of capacity utilization, we assume that labor force participation (the fraction of the working-age population reporting that it is working or looking for work), typically falls in a downturn: potential workers realize their prospects are weak and withdraw from the labor force because they are discouraged or to pursue other goals. As discouraged workers give up searching for job during periods of high

(or rising) unemployment rate, labor force participation generally decreases during recessions.

At the opposite, when the unemployment rate falls, these workers partly reenter the labor force so that labor force tends to rise when the unemployment rate falls.

Finally, we retain the following specification of (the log of) the productivity gap:

$$ag = h(yg, \bar{af}, ad) \text{ with } h_1 > 0, h_2 < 0, h_3 > 0 \quad (6)$$

where  $\bar{af}$  is the growth rate of TFP in the frontier country ( $\bar{af} = \Delta af = \Delta \ln AF$ ) and  $ad$  stands for the distance (or the log of the gap) between TFP in a given non-frontier country and TFP in the frontier country ( $ad = af - a = \ln(AF/A)$ ).

The effects of real GDP growth in equation (6) can be justified by the well-established fact that multifactor productivity growth is partly influenced by the real output gap and tends to move pro-cyclically. According to the labor hoarding hypothesis, if firms face costs in adjusting the size of their workforce, they will tend to allow their utilization of labor to vary over the business cycle instead of completely adjusting their employment of labor in line with fluctuation in product demand. In this case they prefer maintaining excess labor during recessions in order to avoid firing costs and retraining costs associated with new employees. As employment declines less than the produced level of output during downturns, the measured productivity falls.

Because technology transfer and imitation make technological innovation very mobile across countries, technological diffusion across countries is also taken into account by augmenting this simple and conventional specification of pro-cyclical TFP as follows.

We consider that the world can be divided into two groups of countries. Countries in the first group are regarded as technological leaders that are close to the world technological frontier. The second group includes follower countries that are located under the frontier but have the capacity to catch up to the world's frontier. This partition of countries into two groups facilitates an emphasis on the distinction between innovation and imitation as two alternative sources of TFP growth and real output variations. While imitation allows follower countries to catch up to the current world frontier, innovations allows leader countries to improve upon their current local technology and thereby to leap-frog the world frontier. As in Acemoglu et al. (2006), we assume that firms engage both in innovation and adoption of existing technology from the technological frontier. However, while both sources of productivity growth are simultaneously at work in each country, the actual mix of innovation and imitation may influence the ultimate impact of GDP movements on unemployment variations along the business cycle. More precisely, we consider that the process of TFP growth can be decomposed along the following lines in non-leading countries.

First we allow the contemporaneous rate of TFP growth in the frontier to have a direct effect on potential TFP growth in non-frontier countries. Thus, an increase in TFP in the leading countries stimulates the potential level of TFP in follower countries so that the productivity gap widens in these countries, given that the actual level of TFP does not instantaneously and fully converge to its potential level. Second, following the catching-up literature (see for instance Abramovitz, 1986 or Hansson and Henrekson, 1997), we allow the size of innovation in follower countries to be a function of distance from the technological frontier. This assumption amounts to introducing technology transfer and imitation as sources of productivity growth for countries behind the technological frontier. For non-frontier countries, relative TFP, measured as the gap between the frontier and the domestic TFP, is positive.

Hence the more positive is relative TFP, the further a country lies behind the frontier, and the greater the potential for technology transfer.

Inserting equations (4), (5), and (6) into equation (3), the unemployment-output relationship can be rewritten in a more general form as:

$$(u - \bar{u}) = -(1/\alpha) \cdot yg + (1/\alpha) \cdot h(yg, \bar{af}, ad) + f(yg) + (\beta/\alpha) \cdot g(yg)$$

$$\text{or } (u - \bar{u}) = H(yg, \bar{af}, ad) \quad (7)$$

In equation (7) the impact of the output gap on the unemployment gap goes through two distinct channels. The first channel is the direct (or first order) effect of the variation of output on labor demand for given levels of TFP, capacity utilization rate and labor force. It may be considered as the derivative of the optimal demand for labor with respect to output when firms minimize their costs for fixed quantities of the other inputs, at unchanged levels of productivity and when the labor force has not yet reacted to output variations. This first effect may be interpreted as a “beginning of the cycle” reaction. The second effect includes three indirect impacts induced by the underlying influence of movements of the output gap on the variations of the capacity utilization rate, labor force and TFP. As these second order reactions may take some time in the real world, they should be considered as “along the cycle” effects.

### 3. Econometric specifications

In this section, we develop two alternative empirical versions of the theoretical model given by equation (7). However as the literature exhibits several alternative versions of the Okun’s Law relationship with varying associated empirical results, we prefer not sticking to a single empirical version of this model. Moreover, as several papers find evidence of non-linear

relationships between output and unemployment<sup>1</sup>, and since the impacts of the technological gap and the frontier TFP growth rate on the unemployment rate may be highly nonlinear, we will retain two alternative non-linear testable versions of equation (7).

First specification: a second-order Taylor expansion

We first choose to use a second-order Taylor expansion of equation (7) given by:

$$(u - \bar{u})_{it} = \beta_1 y g_{it} + \beta_2 a d_{it-k} + \beta_3 \bar{a} \bar{f}_{it-k} + \beta_4 y g_{it-k}^2 + \beta_5 a d_{it-k}^2 + \beta_6 \bar{a} \bar{f}_{it-k}^2 + \beta_7 (y g_{it} * a d_{t-k}) + \beta_8 (y g_{it} * \bar{a} \bar{f}_{it-k}) + \beta_9 (\bar{a} \bar{f}_{it-k} * a d_{t-k}) \quad (8)$$

Model (8) has the advantage of being general enough to encapsulate several kinds of nonlinear effects and seems to be adequate when the precise form of the underlying nonlinear mechanism is unknown. However, we also have to take into account the fact that there might be unobserved country characteristics, which affect the unemployment gap but that are not captured by our model. Moreover, it is likely that these unobserved country characteristics will be correlated with the explanatory variables in (8). For example, features of the labor market in a country may be partly responsible for a high level of unemployment rate in precisely the countries characterized by a large technological distance to the frontier. In order to control for unobserved heterogeneity that is correlated with the explanatory variables, we thus allow the error term to include a country-specific fixed effect  $\rho_i$ . As there may also be common macroeconomic shocks which affect the unemployment gaps in all countries, the

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<sup>1</sup> For instance Crespo-Cuaresma (2003) use a threshold regression to show that the effect of the output gap on the unemployment gap is larger in recessions than in expansions. Silvapulle et al. (2004) show that the unemployment gap is more sensitive to negative shocks on the output gap than to positive shocks. Holmes and Silverstone (2006) use a Markov-switching model to show that the negative correlation between unemployment and output is still significant in the United States during expansionary regimes.

error term should include a full set of time dummies  $\delta_t$ . The retained empirical version is therefore:

$$\begin{aligned} (u - \bar{u})_{it} = & \beta_1 y g_{it} + \beta_2 ad_{it-k} + \beta_3 \bar{af}_{it-k} + \beta_4 y g_{it-k}^2 + \beta_5 ad_{it-k}^2 + \beta_6 \bar{af}_{it-k}^2 \\ & + \beta_7 (y g_{it} * ad_{it-k}) + \beta_8 (y g_{it} * \bar{af}_{it-k}) + \beta_9 (\bar{af}_{it-k} * ad_{it-k}) + \rho_i + \delta_t \\ & + \varepsilon_{it} \end{aligned} \quad (9)$$

Second specification: OL relationship with threshold

This second specification is aimed at evaluating whether technical change and the technological distance may lead to threshold effects in the GDP-unemployment relationship. Several authors have already shown that threshold effects may be significant in the OL relationship. However, these papers mainly focus on the asymmetric impact of GDP on unemployment depending on the size and the sign of the gap between GDP and potential GDP (see for instance Harris and Silverstone 2001, Silvapulle et al. 2004, Knotek 2007, Virèn 2001) or on the absolute level of the unemployment rate (Malley and Molana 2008).

In order to evaluate whether the processes of technological imitation and innovation generate threshold effects in the OL relationship, we use a threshold model between real output and unemployment variations with technological distance and technical change alternatively considered as potential threshold variables. The retained specification can be written as:

$$(u - \bar{u})_{it} = \tau_1 y g_{it} * I(Z_{it-k} \leq \pi) + \tau_2 y g_{it} * I(Z_{it-k} > \pi) + \rho_i + \delta_t + \varepsilon_{it} \quad (10)$$

where  $I(.)$  is an indicator function which equals 1 (respectively 0) when  $Z_{it-k} \leq \pi$  (respectively  $Z_{it-k} > \pi$ ). In this paper the distance to the frontier ( $ad_{it}$ ) and the growth rate

of the frontier TFP ( $\overline{af}_{it}$ ) are alternatively retained as potential threshold variables, possibly with a  $k$  order lag. As in equation (9), the error term is allowed to include a country-specific fixed effect  $\rho_i$  and a full set of time dummies  $\delta_t$ .

#### 4. Data and empirical results

The data set is taken from the OECD data base and covers 16 OECD countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, UK, and USA. The frequency of the data is annual and the sample period is from 1980 to 2004. Thus it amounts to a total of 400 observations for each variable.

##### *The measure of productivity gaps*

Technical change and distance to the frontier both appear in the two retained specifications of the OL relationship. However, these two variables are non observable. Following Färe et al. (1994), we retain a Malmquist index introduced by Caves, Christensen and Diewert (1982) to measure technical progress and the technical gap between a given country and the technological leader. Using this method a best practice world frontier can be constructed using data on aggregate inputs and outputs of all the countries in the sample. We consider a production set defined by  $F = \{(x, y) \in R_+^{n+p} : x \text{ can produce } y\}$ , where  $y$  refers to a  $p$ -dimensional output vector, and  $x$  refers to a  $n$ -dimensional inputs vector. We assume that  $F$  is a closed set and satisfies the strong disposability and convexity assumptions (see Färe, Grosskopf and Lovell (1985)).

The gap of individual countries from the world frontier is measured by the Shephard output distance function:

$D_0(x, y) = \min \left\{ \theta > 0 : (x, \frac{y}{\theta}) \in F \right\}$ . Then the time change of Malmquist productivity index is defined as:

$$\Delta M_t^o(x_t, y_t, y_{t+1}, y_{t+1}) = \Delta \hat{q}(t) \cdot \Delta \tau(t) \quad (11)$$

$$\text{with } \Delta \hat{q}(t) = \frac{D_{t+1}^o(x_{t+1}, y_{t+1})}{D_t^o(x_t, y_t)} \text{ and } \Delta \tau(t) = \left[ \frac{D_t^o(x_{t+1}, y_{t+1}) D_t^o(x_t, y_t)}{D_{t+1}^o(x_{t+1}, y_{t+1}) D_{t+1}^o(x_t, y_t)} \right]^{\frac{1}{2}}.$$

The subscripts denote the time periods in such a way that  $D_n^o(X_m, Y_m)$   $m, n = t, t+1$ , for example, measures the distance of a country at time period  $m$  relative to the world frontier at time period  $n$ . Each of these distance functions can be estimated through a linear program (see Färe et al. 1994, for details).

The expression in Equation (11) shows that the Malmquist productivity index change between periods  $t$  and  $t+1$  can be decomposed into a product of two component measures: (i) the time change index in technical efficiency ( $\Delta \hat{q}$ ) and (ii) the geometric mean of the technical change index ( $\Delta \tau$ ). Here, the  $\Delta \hat{q}$  variable measures whether production is getting closer to the world frontier constructed as the best-practice frontier for all countries in the sample and the  $\Delta \tau$  variable measures the shift in frontier. Normalizing the initial level to 1 in the base year, the level of Malmquist productivity index is equal to

$$M_t^o = \prod_{s=1}^t (1 + \Delta M^o(s)) = \prod_{s=1}^t (1 + \Delta \hat{q}(s)) (1 + \Delta \tau(s)) \text{ in a given period } t.$$

For the purposes of this paper,  $\Delta \hat{q}$  and  $\Delta \tau$  were evaluated with both constant and variable returns to scale. However, due to space limitation and to the qualitative and quantitative similarity obtained under these alternative assumptions about technology, only empirical results with constant returns to scale are reported and discussed here. Empirical results obtained with variable returns to scale can be obtained from the authors upon request.

Estimation of the Okun's law relationship involves the empirical problem of evaluating the equilibrium (or potential) level of real GDP and the equilibrium (or natural) level of the unemployment rate. As the literature suggests alternative methodologies for measuring these unobserved components of GDP and unemployment, we use three alternative measures of these equilibrium levels: first difference, HP filter (Hodrick and Prescott 1997) and a quadratic time trend.

In order to get a preliminary feeling for the sensitivity of results to the choice of the empirical method retained for evaluating the equilibrium level of the variables, Figure 1 displays scatter plots of the unemployment rate movements (y axis) and real output gaps (x axis) evaluated with these three alternative methods.

Figure 1: cross correlation between unemployment and real GDP movements

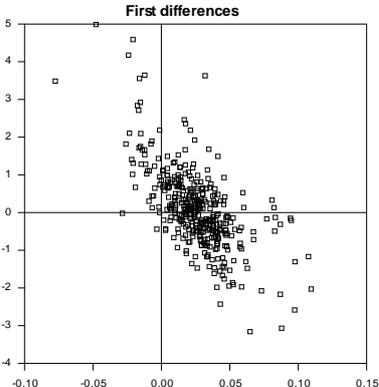


Figure 1 clearly shows that unemployment rate movements are negatively related to real GDP movements with each empirical measure of the equilibrium levels of the variables and provides preliminary evidence in support of the Okun's Law.

In order to complement this visual inspection, Table 1 presents the estimated coefficients for this basic OL model.

Table 1: Estimates of the basic OL equation <sup>(a)</sup>

Filtering and estimating method	P values associated with tests for		$\widehat{\beta}_1$ <sup>(b)</sup>	$R^2$
	Individual effects	Time effects		
Panel A : OLS pooled sample				
First difference	0.731	0.000*	-0.217 (11.219)	0.562
HP filter	1.000	0.013*	-0.350 (16.448)	0.693
Quadratic trend	0.999	0.047*	-0.377 (19.238)	0.689
Panel B : Hildreth-Lu pooled sample				
First difference	0.986	0.000*	-0.203 (9.895)	0.654
HP filter	0.999	0.000*	-0.288 (12.981)	0.819
Quadratic trend	0.988	0.000*	-0.308 (14.511)	0.852
(a) the estimated OL equation is $(u - \bar{u})_{it} = \beta_1 \cdot y_{it} + \alpha_i + \delta_t + \varepsilon_{it}$ (b) absolute values of t tests are in parentheses. * denotes significant at the 5% confidence level				

Panel A is OLS with fixed time effects and fixed individual effects and Panel B is OLS with a Hildreth-Lu correction for first-order serially correlated errors (and with fixed time effects and fixed individual effects). Panel B estimator takes into account a delayed and progressive adjustment mechanism from GDP variation to unemployment movements.

As can be seen in the second column of Table 1, the hypothesis of no individual fixed effects is not rejected by the data with both estimators and every filtering procedure. In contrast, the significance of tests for time effects shown in the third column indicate that omission of time-specific factors may potentially bias Okun's Law coefficients estimates.

Both the OLS and the Hildreth-Lu estimators produce negative and rather similar estimates of the Okun Law coefficient. Estimates obtained with the variables in first difference are systematically lower (in absolute value) than those obtained with filtered variables. However, these values are in the range of the consensus estimate of Okun's coefficient (see for instance Freeman, 2001).

### *The interaction-augmented version*

Model (9) is now estimated with OLS<sup>2</sup>. The selection of the lag  $k$  is data-based and both the values  $k = 0$ , and  $k = 1$  appear to fit the model quite well without dramatic modifications of the estimated results. As with the basic OL relationships, preliminary estimates show that the null of zero individual country fixed effects is never rejected by the data but that fixed time effect are significant. The interaction augmented versions are thus estimated using an OLS pooled sample including time fixed effects. The unemployment and real GDP gaps are evaluated with the Hodrick-Prescott filter. Table 2 shows the initial and the finally retained estimates after deletion of non significant variables.

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<sup>2</sup> Due to space availability, only empirical results obtained with the HP filtered series will be displayed. Empirical results obtained with first differences or with quadratic time trend are qualitatively and quantitatively comparable and can be obtained from the authors upon request.

Table 2: Regression estimates with the interaction-augmented model

Regressors	OLS pooled sample estimates			
	Model with $k = 0$		Model with $k = 1$	
	initial equation	final equation	initial equation	final equation
$yg_{it}$	-0.230 (8.66)	-0.237 (9.17)	-0.234 (8.50)	-0.239 (8.84)
$yg_{it}^2$	0.002 (0.71)		-0.001 (0.32)	
$ad_{it-k}$	-0.019 (1.31)		-0.023 (1.50)	
$ad_{it-k}^2$	0.001 (0.91)		0.001 (1.61)	
$\bar{a}f_{it-k}$	0.040 (1.02)		0.034 (0.85)	
$\bar{a}f_{it-k}^2$	0.002 (0.28)		0.018 (1.73)	
$(yg_{it} * ad_{it-k})$	-0.016 (6.97)	-0.015 (7.02)	-0.015 (6.50)	-0.015 (6.58)
$(yg_{it} * \bar{a}f_{it-k})$	0.026 (2.33)	0.024 (2.47)	0.035 (2.91)	0.026 (2.36)
$(ad_{it-k} * \bar{a}f_{it-k})$	-0.009 (2.40)	-0.007 (2.28)	-0.001 (0.24)	
P. value F test	0.622 <sup>(a)</sup>		0.385 <sup>(b)</sup>	
R <sup>2</sup>	0.740	0.738	0.737	0.733

(a) F test for  $H_0 : (\beta_2, \beta_3, \beta_4, \beta_5, \beta_6) = (0, 0, 0, 0, 0)$ . (b) F test for  $H_0 : (\beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7) = (0, 0, 0, 0, 0, 0)$

The OL coefficient is negative and significant in all specifications. In contrast, the squared variables never appear as significant so that potential non linear effects from GDP to unemployment do not seem to be adequately captured by these squared terms (including the squared real GDP gap). The null hypothesis of no interaction effects is systematically rejected for the cross effects GDP gap-distance to the frontier and GDP gap-technical change. An interaction effect between technical change and the distance to the frontier cannot be excluded for the model estimated with  $k = 0$ .

The coefficient associated with the variable picking up interaction between the GDP gap and distance to the frontier is negative while the coefficient associated with the interaction term GDP gap-technical change is positive.

The negative and significant coefficient associated with the GDP gap-distance to the frontier interaction term suggests that the impact of GDP gap movements on unemployment rates is

larger when the lagged value of the distance to the technological frontier is large. This contrasts with the positive coefficient associated with the cross term GDP gap-technical change, showing that the impact of GDP gap movement on unemployment is mitigated when technical change is a large source of GDP variations.

By calculating the derivative of the unemployment variation with respect to the GDP gap, empirical results in Table 2 show that the impact of a 1% rise in actual real output (relative to its potential) on unemployment variation is close to  $-0.237 - 0.015 * ad_{it} + 0.024 * \bar{af}_{it}$  with  $k = 0$  and to  $-0.239 - 0.015 * ad_{it-1} + 0.026 * \bar{af}_{t-1}$  with  $k = 1$ .

These cross effects are similar and may appear as rather limited but they can be interpreted as follows. The total effect of a 1% rise in output on unemployment variation is twice the first order effect for a technological distance close to 16% (for  $k = 0$ ,  $0.237/0.015 = 15.8$  and for  $k=1$ ,  $0.239/0.015 = 15.9$ ). In contrast, the impact of a 1% rise in output on unemployment variation is zero when technical change is close to 9.9 % with  $k = 0$  and to 9.2 % with  $k = 1$ . Very rapid increases in the rate of technical change can thus lead to a reversal of the traditional effect on unemployment movements.

Evaluating the across country average OLC using the across country mean values of  $ad_{t-k}$  and  $\bar{af}_{t-k}$  leads to a multiplier effect of GDP gap variations on the unemployment gap close to  $\Delta(u - \bar{u})/\Delta yg = -0.337$  with  $k = 0$  (and  $\Delta(u - \bar{u})/\Delta yg = -0.339$  with  $k = 1$ ). Note that these two multiplier effects perfectly match the standard empirical values of the OLC reported in the literature. Our estimated model shows that the first order effect (as measured by  $\hat{\beta}_1$  in equation (9)) corresponds to approximately 70% of this multiplier effect (both with  $k = 0$  and  $k = 1$ ). Thus, following a shock on the GDP gap, only two third of the observed subsequent variation in the unemployment gap can be attributed to the standard theoretical

effects of labor hoarding and the reaction of the demand for labor. The remaining part of the reaction of the unemployment gap stems from the nonlinear effect of the distance to the frontier and the rate of growth of technical change. These nonlinear effects vary for each country with its technological frontier distance and the growth rate of its potential output.

Many papers show that the OLC is unstable both over time and over the business cycle (see for instance Crespo-Cuaresma, 2003 or Huang and Lin, 2008). Taking into account the previous empirical results, this instability might be partly explained by the fact that the net impact of GDP movements on unemployment in a given country  $i$  is the sum of two underlying effects: a “first order direct” effect that can be interpreted in the spirit of the traditional OL coefficient and a nonlinear effect through the interaction of GDP with both the size of the technological distance of country  $i$  and the displacement of the technological frontier.

As the distance to the technological frontier may change over time due to the path of private and public investments (such as infrastructures or education) or to the movements of the innovation capacity of leader countries, the interaction effect may also change, thereby increasing or decreasing the global impact of GDP variation on unemployment.

In addition to temporal instability, it has also been argued that the OLC varies over space. This may also be, at least in part, attributable to differences between countries in distance from the technological frontier.

As can be seen, the first order direct effect is still interpretable as a demand side effect induced by the difference between the level of aggregate demand and the production potential of the country. In contrast, the cross (or interaction) impacts are supply side effects, induced by the relative cost of technological improvements through innovation or imitation. While standard macroeconomic theory strongly suggests that technological improvements

significantly impact the labor market and ultimately unemployment only in the long-run, these nonlinear versions of the OL relationship clearly show that significant effects may be present in the short run also.

### *The threshold effect version*

The hypothesis that interacting effects induced by technical change and technological distance may be present in the unemployment-GDP relationship is now reexamined by assuming that these variable may create threshold effects in the OL relationship. Tests for threshold effects are performed with equation (10) by using the statistical procedure developed by Hansen (1999) for non-dynamic panels. After estimating equation (10) and calculating the sum of squared residuals (SSR) for any given  $\pi$  (denoted  $S(\pi)$ ), the least square estimator of the threshold is obtained as  $\hat{\pi} = \frac{\text{Argmin}}{\pi} S_1(\pi)$ . Hansen suggests a bootstrap method to simulate the asymptotic distribution of the likelihood ratio test  $LR = (S_0 - S_1)/\hat{\sigma}$  where  $S_0$  is the sum of squared errors under the null of no threshold and  $\hat{\sigma}$  is the residual variance under the alternative.

OLS pooled sample estimates of equation (10) with time fixed effects is performed by allowing for successively zero, one and two thresholds. The distance to the frontier and technical change are alternatively used as threshold variables. Empirical results are reported in Table 3. A preliminary empirical search suggests that using a lagged value for the threshold variables is more appropriate than using a contemporaneous value, so that  $k = 1$  is retained in equation (10).

Table 3: Tests for threshold effects and regression slopes

Threshold variable	Threshold values ( $\hat{\pi}$ )	SSR	Test (P value)	$\tau_1$ (t stat)	$\tau_2$ (t stat)
<i>Test for single threshold</i>					
<u>Threshold variable :</u>					
$\widehat{ad}_{it-1}$	2.659	154.204	109.39* (0.0018)	-0.230* (8.95)	-0.453* (19.24)
$\widehat{af}_{it-1}$	0.673	168.034	65.922* (0.000)	-0.386* (17.08)	-0.232* (5.90)
* : significant at the 5% confidence level, ** : significant at the 10% confidence level					

The test statistics along with their bootstrap P values (10000 bootstrap replications were used for each of the four bootstrap tests) show that both tests for a single threshold and for a double threshold are strongly significant with distance to the frontier as the threshold variable but that only the test for a single threshold is significant when technical change is used as the threshold variable. We conclude that there might be two separate thresholds in equation (10) with distance to frontier as the threshold variable but that only one threshold might be retained with technical change as the threshold variable.

It is interesting to examine the SSR sequences (presented in Appendix 2) which are computed when estimating single and double threshold models. Examining first the results obtained with distance to the frontier as the threshold variable shows that the first-step threshold estimate is the point where the SSR sequence reaches its minimum value at  $\hat{\pi} = 2.659$ . The regression slope estimates and conventional OLS t-statistics are displayed in the last three columns of Table 3. The point estimates obtained with the single threshold model suggest that the larger the distance to the frontier, the larger the short term impact of GDP gap movements on unemployment variations (in absolute terms).

Turning to the SSR sequences obtained with technical change as the threshold variable show that the threshold estimate is the point where the SSR sequence reaches its minimum value at

$\hat{\pi} = 0.673$ . As a precise examination of multiple thresholds is beyond the scope of this paper, we limit our analysis to the case of the single threshold. The point estimates obtained with the single threshold model suggest that the larger is the technical change potential, the smaller the short term impact of GDP gap movements on unemployment variations (in absolute terms).

Taking results for both threshold variables together, we observe that the estimated values of the  $\tau_1$  and  $\tau_2$  coefficients (and the associated conventional OLS t statistics) reported in Table 3 are qualitatively consistent with the empirical results obtained with those reported in Table 2 for the previously estimated non-linear version of the OL model. The effect of GDP movements on unemployment appears to be negative and significant in both regimes but the sensitivity of unemployment to GDP gap movements is smaller (in absolute value) when the size of technical change is large but is larger when the technological gap is above the estimated threshold. The quantitative influences of technical change and the technological gap, as revealed by the estimates of  $\tau_1$  and  $\tau_2$ , are now lower than those evaluated with the interaction-augmented model. According to Table 3, the GDP-unemployment correlation nearly doubles and changes from -0.230 to -0.453 when the technological gap becomes larger than 2.66%. With such a technological gap, the absolute value of the Okun's Law coefficients only increases by 17% according to the empirical estimates of the interaction model. Considering the influence of technical change, Table 3 reveals that the impact of real output on unemployment is divided by 1.67 when the growth rate of technical change becomes larger than 0.67 %. According to Table 2, the Okun's Law coefficient only changes from -0.237 to -0.220 (so that it is divided by 1.07) when growth rate of technical change equals 0.67 %. These empirical discrepancies may be partly attributed to the differences of the two retained empirical methodologies since the threshold procedure might widen the gap between the estimated effects for each regime.

Keeping in mind this sensitivity of the empirical result to the retained methodology, both statistical strategies clearly show that the responsiveness of unemployment variations to GDP movements is positively correlated with the technological distance to the frontier and is negatively correlated with the growth rate of technical change.

A labor hoarding perspective might enable one to interpret these empirical results. According to the labor hoarding hypothesis, firms prefer keeping unneeded workers during recessions if they expect that the drop in demand will be temporary and if hiring new workers is costly. In this case, labor hoarding will lead to higher costs in the short run, but lower costs in the long run. Beside this fairly general theoretical result which underlies nearly all empirical estimates of the OLC, our empirical results suggest that we also have to take into account the fact that while hiring cost are partly incurred through advertising, interviewing and selecting activities, the largest part of hiring costs is induced by firm-specific training. Moreover, while *general* human capital is useful to all firms, *firm-specific* human capital is only useful for one firm. Firms using mainly firm-specific human capital might thus prefer not firing workers during a recession simply because they expect that hiring and training new workers will be costly when aggregate demand will start rising again. In contrast, firms using mainly general human capital (such as construction, for example) may lay off a large part of its employees in a recession then just hire new workers when aggregate demand is rising.

As the kind of firm which mainly uses specific human capital is generally thought to be located in countries or regions lying close to the technological frontier, the size of the labor hoarding effect may be expected to be larger when the technological distance is small and when the growth rate of technical change is high. Symmetrically, in this case, the absolute value of the OLC is larger (smaller) when the technological distance is large (small) and when

the growth rate of technical change is low (high). This might explain some of our empirical results.

Moreover, our results are consistent with those put forth by Huang and Lin (2008) which find that the trade-off between unemployment rate and real output movements is negatively associated with lagged trend productivity growth (which may allow firms to raise output without as much new labor in the case of rapid productivity growth).

Countries essentially engaged in innovation and which lay very close to the technological frontier exhibit high growth rates of productivity and mainly use specific human capital.

According to our results, these countries should exhibit high degrees of labor hoarding, and simultaneously a low (absolute) value of the OLC.

## **5. Conclusion**

The OL relationship between GDP movements and unemployment variations is revisited by taking into account the influence of technical change on GDP variations. We separate technical change in a given country into a component corresponding to the variation of the world technological frontier and a component consisting of variation in the distance between the technological level of this country and the world frontier. This decomposition permits one to show that variations of real GDP movements lead to stronger effects on unemployment decreases in countries exhibiting a large distance to the frontier. In contrast, GDP movements induced by shifts in the world technological frontier lead to reduced effects on unemployment. This empirical result may help explain why the Okun's Law appears to be unstable over time and over the business cycle. Moreover, GDP increases induced by catching-up to the leader effects result in significant reductions of the unemployment rate.

Finally, these results show that technological distance and factors affecting it (such as innovation, technology adoption, investment, or industrial specialization) might be considered as key elements for explain unemployment-output correlation discrepancies across countries.

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**Appendix 1:** Chow tests for breaks in the basic OL relationship

Table A1 : Chow tests empirical results

	<b>P.values associated for Chow tests for sample splitting</b>			
Subsample 1	1980-1984	1980-1989	1980-1994	Zero technical distance
Subsample 2	1985-2004	1990-2004	1995-2004	Nonzero technical distance
First difference	0.819	0.628	0.203	0.000
HP filter	0.062**	0.051*	0.892	0.000
Quadratic trend	0.016*	0.018*	0.385	0.000

**Appendix 2: SSR sequences calculated for threshold regression methods**

