

Okun's law – A meta analysis

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1 INTRODUCTION

Since the pioneering work of Okun (1962) and his famous result that a 3% increase in output is associated with a 1% decline in the rate of unemployment, a large stream of literature has been devoted to the so-called Okun's Law, the responsiveness of the unemployment rate to real output variations. As the Okun's Law coefficient (OLC hereafter) continues to be a central parameter in the field of short run macroeconomics, it is not surprising that the empirical component of this literature has reported a proliferation of estimates of the correlation between unemployment and real GDP movements.

To date, however, no consensus has been reached regarding the size of the OLC, and several alternative theoretical models and empirical strategies have been used for estimating its value. However, empirical estimates are often sensitive to model specification and particularly to whether output or unemployment is used as the dependent variable. Other forms of differences in model specification arise from the choice about use of a static or dynamic model; and from the choice about use of first-difference (with output and unemployment variables expressed in first differences) or gap model (with output and unemployment variables expressed in terms of the cyclical components or deviations from long-term trends). In the case of the gap model, empirical results may also be sensitive to the choice of the detrending method (linear trend, HP filter, etc.).

While this literature is characterized by a diversity of models and empirical strategies and by a striking heterogeneity of empirical results, no systematic survey has been done. This diversity of models, empirical strategies, and results makes it difficult to use these estimated OLC values for the practical analysis of short run macro fluctuations.

Moreover, as suggested by DeLong and Lan (1992), publication bias can be found in several fields of economic research and may thus potentially concern empirical analysis of the Okun relationship. Two forms of publication bias are of particular interest in the present context. One form will exist if the process of research publishing predominantly selects papers with statistically significant results. Hence, larger and more significant effects will be over represented while studies with small insignificant effects will be under represented or won't be published. This form of bias – where statistically significant results are preferred – is known as type II bias. A second form, known as type I bias, occurs where a particular direction of results is preferred.

With publication selection, one would expect the average of effect magnitudes across papers to be upwardly biased, and so the presence of large empirical effects in the literature would not be statistically well-founded (Stanley 2005). Without correction for publication bias, it is not valid to take summary statistics of large empirical effects found the literature as indicative of true population values of the effect in question. It follows that if the Okun's Law literature has been subject to publication selection bias, averages of OLC estimates across papers are likely to be upwardly biased in magnitude (in absolute value) and so will be invalid as evaluations of the true value of the OLC.

Economists have already tried to use meta regression analysis to test for publication selection and then to remove or lessen its effects (beginning with Stanley and Jarrel, 1989). One of the main aims of this paper is to use meta regression analysis (MRA hereafter) to study whether the observed variation in OLC may be partly accounted for by the existence of such publication biases¹. To the best of our knowledge, this is the first paper which performs a meta regression on Okun's law. Okun's Law is widely used as a rule of thumb for assessing

¹ While meta analyses are often used in the field of medicine with independent individual studies, empirical studies on the Okun's Law sometimes use non independent data sets including for example the US unemployment rate. However, as the starting and ending periods of the data base, together with the data frequency or the transformation of variables vary a lot across studies, the finally estimated results of these studies may be reasonably considered as independent from each other and included in a meta analysis.

the expected level of the unemployment rate, and the reliability of any such assessments should be improved if estimated values of the OLC are corrected for significant evidence of publication bias.

Christophe: In the next paragraph, the term “multivariate” MRA is used. But to this point there has been no mention of **bivariate** MRA (just MRA). Should there have been? On a related point, I think we need some wording about why we do bivariate MRA to examine publication bias, but then later use multivariate MRA to estimate the true OLC (as one of the referees raises this point).

We then perform a multivariate MRA by including ‘moderator’ dummy variables in an attempt to establish whether variations in OLC across studies are mainly due to data characteristics or to different model specifications. As the choice of real output or unemployment as dependent variable is a notable aspect of heterogeneous specifications in the empirical literature on the Okun’s Law, this choice may be expected to influence empirical estimates of the OLC (except if there were one cointegrating relationship between unemployment and real output, which is not found in the literature). Hence, we will investigate the influence of this specification choice by running separate investigations for the subset of studies using real output as the dependent variable and for the subset of papers using unemployment as the endogenous variable.

Our results can be summarized as follows. First, there is evidence of type II bias in both sub-sets, but a type I bias is present only among the papers using some measure of real output as the dependent variable.

Second, after correction for publication bias, statistically significant OLC effects are present in both sub-sets. Third, bias-corrected estimated OLCs are significantly lower (in absolute value) with models using some measure of unemployment as the dependent variable. Using a bivariate MRA approach, the estimated true effects are -0.25 and -0.61 for the unemployment sub-set and the output-sub sample respectively; with a multivariate MRA methodology, the estimated true effects are -0.40 and -1.02 for the unemployment and the output-sub samples respectively.

The paper is structured as follows. Section 2 briefly reviews the main issues in the empirical research on the Okun’s Law. Section 3 describes the properties of the literature sample used for the meta analysis. Section 4 explains our approach to implementing the MRA. Section 5,

using graphical analysis and bivariate MRA, tests for the existence and magnitude of publication bias. This permits the authors to estimate (one or more) ‘authentic’ Okun’s Law coefficient beyond publication bias. The corresponding multivariate MRA is conducted in Section 6. Section 7 concludes.

2. THEORETICAL BACKGROUND

Since Okun’s (1962) seminal paper, Okun’s law has widely been accepted in the literature as a representation of the negative relation between unemployment and output. In his 1962 article, Okun presented two simple equations connecting the rate of unemployment to real output which have frequently been used as rules of thumb for applied macroeconomic analysis. Since that time, these equations have been expanded on and modified by many authors so as to improve statistical fit and to make their theoretical foundation more precise.

A first group of papers includes two classes of specification suggested by Okun (1970): the first difference model and the ‘gap’ model. According to the first-difference model, the relationship between the natural log of observed real output (y_t) and the observed unemployment rate (u_t) is given by the expression

$$\Delta u_t = a_0 + a_1 \Delta y_t + \varepsilon_t \quad (1)$$

where a_0 is the intercept, a_1 ($a_1 < 0$) is Okun’s coefficient measuring by how much changes in output produce changes in the unemployment rate, and ε is the disturbance term.

From the point of view of the gap model, the specification is given by the expression

$$u_t - u_t^* = b_0 + b_1(y_t - y_t^*) + \varepsilon_t \quad (2)$$

where y^* represents the log of potential output, u^* is the natural rate of unemployment and the other symbols have the same meaning as in equation (1). In this second specification, the left-hand side term represents the unemployment gap, whereas $(y_t - y_t^*)$ captures the output gap. In other words, the difference between the observed and potential real GDP captures the

cyclical level of output. Likewise, the difference between the observed and natural rate of unemployment represents the cyclical rate of unemployment.

A major problem with the gap model is that there are no observable data on y^* and u^* so they have to be estimated. While Okun retained $u_t^* = 4\%$ as a target rate of labour utilization and favored a simple time trend to measure y_t^* , alternative time series approaches have been proposed in the literature for estimating y_t^* and u_t^* . Among others, deterministic methods such as the Hodrick-Prescott filter (see for instance Marinkov and Geldenhuys 2007, or Moosa 2008) or the Baxter-King filter (see for instance Villaverde and Maza 2009) have been widely used while some authors selected stochastic decomposition procedures such as Beveridge and Nelson (see for instance Lee 2000) or the unobserved components model suggested by Harvey (1989) and estimated with a Kalman filter algorithm (see for instance Moosa 1997, or Silvapulle et al. 2004). Finally, some papers use a specific auxiliary model to estimate these equilibrium values (see for instance Prachowny 1993, or Marinkov-Geldenhuys 2007).

As Okun noted that one of the shortcomings of the proposed relationship lies in the fact that the unemployment rate may only be considered as a proxy variable for idle resources affecting output losses, a second group of papers built empirical versions of the Okun's Law from a macroeconomic production function relating real output to a set of factors potentially including labour, capital, and technology (see for instance Gordon, 1984). Assuming that equilibrium real output is obtained when all factors reach their equilibrium level, the production function can then be transformed into a gap version of Okun's Law including the idle resources coming from each input and which can be written as :

$$y_t - y_t^* = c_0 + c_1(u_t - u_t^*) + c_2(Z_t - Z_t^*) + \varepsilon_t \quad (3)$$

where $(Z_t - Z_t^*)$ is a vector of gaps between equilibrium and observed values of inputs other than labour. It is important to note that this kind of production function-version of the Okun's Law is then estimated with real output as the dependent variable instead of the unemployment rate.

Theoretically and econometrically, this reversal of the functional form of the estimated relationship makes it difficult to compare the empirical results found with the two groups of studies: one group in which the unemployment change or gap is the dependent variable; the

other obtained using the production function version of the Okun's Law. It is well-known that the coefficient of a regression of X on Y is not in general equal to that in the inverse of a regression of Y on X. However, to make both groups of OLC estimates interpretable as the sensitivity of unemployment to real output changes, and so to facilitate comparison across the two groups of studies, coefficients estimated with equations using real output as the endogenous variable were systematically inverted, thereby rewriting all OLC values as the effect of real output variations on unemployment movements.

3. META ANALYSIS: LITERATURE SAMPLING

Here we describe the procedure retained for literature sampling for the meta regression analysis. In order to select a sample of OLC empirical studies which is both representative of this literature and of a manageable size, we have resorted to a structural search for articles using the following sampling criteria. First, we searched the EconLit database for empirical studies on the OLC and all the papers that fulfilled the following criteria have been selected: (i) key words used in the search were: "Okun's Law" and "Output-unemployment relationship"; (ii) an abstract is presented so that the presence of econometric estimations of the OLC can be checked; (iii) the article was published after 1980 and was listed in the EconLit database as of December 2010.

1980 was retained as the starting date in order to permit analysis of the variance of published OLC empirical estimates but within relatively unified econometric frameworks and with data sets of the same quality and with reasonable time lengths. Dynamic time series methods with regards to data transformation, data stationarity, and optimal lag selection became increasingly common in the eighties. Prior to 1980, many papers used very short data series (for instance, Thirlwall, 1969, used annual data from 1950 to 1967 with just 18 data points) or statistically-questionable methods (such as empirically estimated time trends or *ad hoc* coefficients in order to calculate potential output or the natural rate of unemployment). All papers not related to the research question have been excluded. This selection process identified 97 papers.

After having examined these 97 articles, we excluded studies that do not include any original econometric estimation of the Okun's Law coefficient. We also excluded studies that do not give sufficient information concerning the type of estimated model (endogenous/exogenous

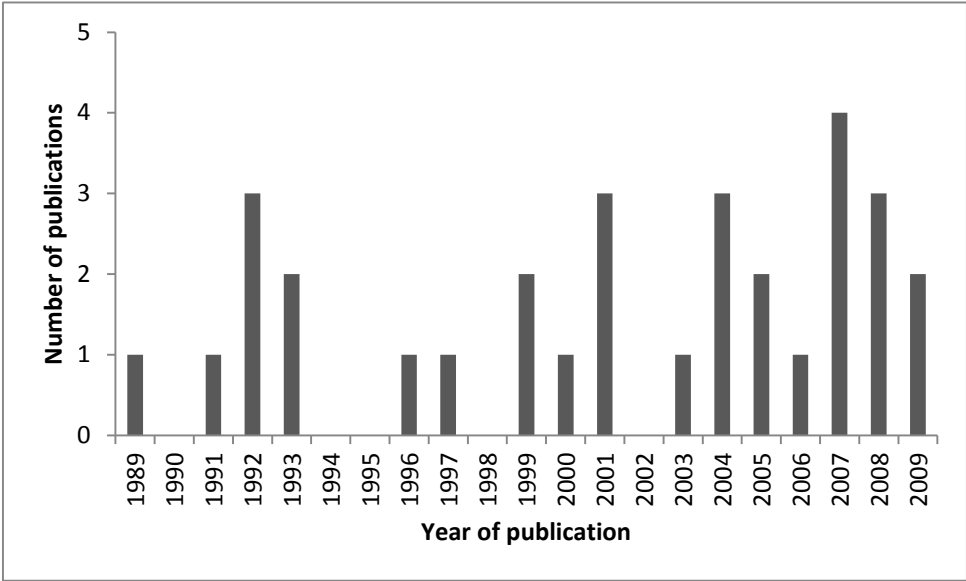
variables), the data base (initial and final dates, periodicity) or the empirical results (R-squared value, estimated coefficients and standard errors). We decided to exclude studies including only non linear Okun's Law models.² Finally, it is important to note that while some studies suggest that Okun's law has undergone structural change over time (e.g. Lee (2000), Huang and Chang (2005), Sögner and Stiassny (2002)), over countries (Kaufmann (1988), Lee (2000), Moosa (1997)) or over the course of the business cycle (e.g. Crespo-Cuaresma (2003), Huang and Chang (2005), Silvapulle et. al (2004)), we decided to restrict our data base to linear versions of the Okun's relationship assumed to be stable across the whole data sample. This choice was motivated by the following reasons. First, these studies predominantly use either non linear models such as threshold models which include ad hoc assumptions concerning the threshold variable (the previous level of unemployment or the previous growth rates of real output for instance) or time varying models where empirical results may appear highly dependent upon the characteristics of the retained methodology (the size of the rolling window, for example). Incorporating these papers in the data base would thus go in hand with a large increase of the set of conditioning variables in the multivariate meta regression model with a limited number of observations associated with each variable. Second, due to the sensitivity of the estimated results to the retained testing procedure, these papers often lead to heterogeneous results and may give rise to controversies (see for instance the recent debate between Owyang and Sekhposyan (2012) and Ball, Leigh and Loungani (2012) on the stability of the Okun's Law relationship during the Great Recession).

As a consequence, while the comparison of the empirical results produced by linear and nonlinear models within a meta regression analysis may constitute an interesting area of research, it seemed *a priori* difficult to include both linear model and heterogeneous non linear models within the same meta regression sample. The total number of studies left after

² One referee suggested that, by excluding non-linear Okun's Law studies, this paper may suffer from publication bias of its own. In any meta regression analysis there are necessarily choices that have to be made regarding the criteria for inclusion of studies being considered in the MRA. As explained above, we have used several such inclusion criteria. The reason why we have excluded studies which only estimate non-linear models is a practical one: the results of such studies cannot easily be compared with those from linear models within the confines of a MRA. A MRA encompassing non-linear Okun's Law studies (and comparing those with results from linear models) would be an interesting item for future research.

applying these criteria was 28 and the total number of observations in our database is 269, each corresponding to one regression. Figure 1 shows the “life cycle” of this literature in terms of the number of documents recorded in EconLit and retained in the present MRA.

Insert Figure 1 near here (Caption: The number of retained EconLit publications on the OLC)



As can be seen, the average number of papers meeting our selection criteria increased after 2003 and the literature peaked in 2007. Even base specifications of the Okun’s Law model permitted more than one regression per study since this specification is often applied to different samples, different time periods, and different measure of the output gap or of the variation of the unemployment rate around its equilibrium level. In accordance with common practice in meta regression analysis, these were recorded as independent regressions in order to investigate the influence of these heterogeneities on the published effect. The full list of studies included in the MRA is given in the list of References at the end of this paper (each being marked by an * symbol).

Insert Table 1 near here. Caption: Descriptive statistics of OLC studies (28 studies) and OLC estimates (269 estimators)

	Minimum	Maximum	Mean	Standard deviation	Median
OLC	-3.22	0.17	-0.77	0.71	-0.58
Number of observations	21	408	50.4	46.54	41
First year	1948	1990	1968.2	10.75	1970
Last year	1985	2006	1999.2	4.61	1999
<u>Proportion of OLC estimators with the following features (%)</u>					
Time series data base		98.9	Country		74.0
Panel data base		1.1	Region		26.0
Yearly frequency		68.5	European countries		74.4
Frequency higher than year		31.5	Unites States		7.6
Endogenous variable : Unemployment rate		41.8	Rest of the world		18.0
Endogenous variable : Real output		58.2	Static model		53.6
Model in level		9.2	Dynamic model		40.0
Model in first difference		14.7	Cointegrated model		6.4
Equilibrium values of real output and unemployment from filtering procedure		76.1			

Table 1 presents salient characteristics of the papers retained for our MRA. The number of observations used in the OL equations varied enormously. The smallest was 21, while the largest was 408. All but 1.1% of the OLC were estimated from time series data bases and more than half of the studies (68.5%) used annual frequency. Nearly three quarters of the papers use country level data while the remaining papers use regional data bases. The percentage of estimates obtained with either the gap or the first difference version of the OL equation (41.8%) is close to the percentage of estimates obtained with production function versions of the OL (58.2%).

4. THE META ANALYSIS FRAMEWORK: TESTING FOR PUBLICATION BIAS AND ESTIMATING THE TRUE COEFFICIENT

The process of academic publishing may influence the characteristics of the published results. While several kinds of publication biases can appear, two specific biases are most often encountered (Stanley, 2005). Type I bias occurs when editors, referees, and/or researchers have a preference for a particular direction of results. Positive estimates of the OLC, for instance, might be ignored as it seems implausible that short run movements of unemployment are positively correlated with output gap fluctuations. However, even if there are very strong theoretical reasons for expecting negative estimates of the OLC, at least a few studies should report positive estimates. We can, for example, imagine the case of specific labour market regulations in case of macroeconomic downturns. A positive OLC finding may also arise due to some characteristics of data sets or of empirical methodologies. Such a bias would make the average taken from the published literature larger (in absolute value) than the estimated true effect.

Type II bias arises when editors, referees, and/or researchers have a preference for results that are statistically significant. As smaller samples and limited degrees of freedom reduce the probability of finding a significant result, this kind of publication bias may appear when researchers using small samples are inclined to search across econometric “tools” (proxies, estimators, specifications) in order to produce more significant results. Type II selection will thus lead to excess variation (Stanley, 2005).

Detection of the presence of type I publication bias most commonly starts with the so-called funnel plot which compares the effect size for each regression (here the OLC) against some measure of its precision (the inverse standard error of the OLC, Egger et al. 1997). In the case of no bias, the plot should appear as an inverted funnel: observations with high precision should be concentrated closely to the true effect, while those with lower precision should be more spread at the base of the plot. In the absence of type I publication bias, the funnel plot is thus symmetric.

This visual investigation can also be supplemented with explicit regression tests. The funnel asymmetry test (FAT) due to Egger et al. (1997) is implemented by means of the regression:

$$OLC_i = \alpha + \beta \cdot SE_i + u_i, i = 1, \dots, N \quad (4)$$

where OLC_i is the i^{th} estimate of the OLC, SE_i is the standard error of point estimate i , N is the number of estimates of the OLC and u_i is the regression error term. In this simple MRA, α denotes the true OLC, and β indicates the size of publication bias.

As regression (4) is heteroskedastic and the measure of heteroskedasticity is the standard error of the estimate of the OLC, Stanley (2008) suggests performing weighted least squares by dividing equation (4) by the standard error of the OLC. This is simply achieved by OLS estimation of the transformed regression equation:

$$\frac{OLC_i}{SE_i} = t_i = \beta + \alpha \cdot \left(\frac{1}{SE_i}\right) + v_i, i = 1, \dots, N \quad (5)$$

where t_i is the t -statistic measuring the significance of the i^{th} OLC. Equation (5) represents a regression line through a funnel graph which is rotated by 90 degrees and which is adjusted for heteroskedasticity. The FAT test for publication bias is then a simple t -test on the intercept of equation (5); a β significantly different from zero indicates the presence of publication bias. If β is significantly positive (or negative), then the effect size is subject to an upward (or downward) bias. Moreover, there is evidence of a “true” empirical effect (that is, a systematic relationship between unemployment variation and real output movements) if the coefficient α is significantly non-zero.

As the process of selecting estimates from the literature makes meta-analysis highly vulnerable to data contamination, the robustness of this basic test is checked by re estimating equation (5) with the iteratively re-weighted least squares method (IRLS) as in Krassoi Peach and Stanley (2009) or Havranek (2010).

In a similar way to the case of the type 1 bias, a visual inspection for the presence of type II bias can be assessed using the Galbraith plot (Galbraith 1988). This consists of a scatter diagram of the precision of the estimates of the OLC against the t -statistics corresponding to those estimates for a given assumed value of the true effect. If there were type II selection, large values (in absolute terms) will be over reported and there will be an excessive likelihood of reporting significant results. In case there was no type II publication bias and the true effect (labeled TE) were really true, the statistics $|(OL_i - TE)/SE_i|$ should not exceed 2

more than 5% of the time and the cloud should be randomly distributed around 0, with no systematic relation to precision.

The method of testing for type I bias can also be used to test for significance of the true effect beyond publication bias. The precision effect test (PET) is a simple t -test on the slope coefficient α of equation (5).

As one of the main objectives of most meta analyses is to determine the dependencies of empirical results on characteristics of empirical strategy and design, we finally (in Section 6) use the general multivariate version of the FAT-PET method which is specified as follows:

$$\frac{OLC_i}{SE_i} = t_i = \beta + \alpha \cdot \left(\frac{1}{SE_i}\right) + \sum_{k=1}^K \gamma_k \cdot \left(\frac{Z_{ki}}{SE_i}\right) + \omega_i, i = 1, \dots, N \quad (6)$$

where Z_{ki} , $k = 1, \dots, K$ are meta-independent variables assumed to potentially affect the estimate of the OLC and ω_i is the meta regression disturbance term, which has the standard characteristics. Each of the Z_{ki} is weighted by $(1/SE_i)$ and the γ_k are K coefficients to be estimated, where each one measures the impact of the corresponding variable on the OLC.

The meta-independent variables used in this paper are presented in Table 2. We focus on a set of variables constructed to represent the following characteristics of models used in the Okun's law empirical literature. Regarding the influence of sample features on empirical results we concentrate on the initial and final dates (respectively FIRSTYEAR and LASTYEAR) of the studies (and a variable constructed as the central point of the sample period used, AVGYEAR); we distinguish between time series data (SAMPTS) and panel data (SAMPPA); between samples dealing with annual data (FREQY) and semestrial or quarterly data (FREQSQ); between samples using country-level (COUNT) or regional-level (REG) data sets; and finally between papers that focus on OECD countries (OECDCOUNT) and papers centered on non OECD countries (NOECDCOUNT). While there may be variance across countries within each of the OECD and non OECD groups, these dummies control for a variety of institutional characteristics (such as property rights regimes and labour mobility conditions) that may differ systematically between, but not within, the two groups.

Insert Table 2 near here. Caption: Description of potential explanatory variables

Variables	Description of the variable
FIRSTYEAR	First year of the sample
LASTYEAR	Last year of the sample
SAMPTS	Dummy, 1 if the study uses a time series data base, 0 otherwise
SAMPPA	Dummy, 1 if the study uses a panel data base, 0 otherwise
FREQY	Dummy, 1 if the study uses annual data, 0 otherwise
FREQSQ	Dummy, 1 if the study uses semestrial or quarterly data, 0 otherwise
COUNTDED	Dummy, 1 if the data base only includes developed countries, 0 otherwise
COUNTDING	Dummy, 1 if the data base only includes developing countries, 0 otherwise
COUNT	Dummy, 1 if the data base only includes countries, 0 otherwise
REG	Dummy, 1 if the data base only includes regions, 0 otherwise
MODSTA	Dummy, 1 if the model is static, 0 otherwise
MODDYN	Dummy, 1 if the model is dynamic, 0 otherwise
OTHEXO	Dummy, 1 if the model includes other exogenous variables than the unemployment variable or the GDP variable, 0 otherwise
NOOTHEXO	Dummy, 1 if the model includes no other exogenous variables than the unemployment variable or the GDP variable, 0 otherwise
NEQ1	Dummy, 1 if the model includes a single equation, 0 otherwise
NEQN	Dummy, 1 if the model includes several equations, 0 otherwise
ENDU	Dummy, 1 if unemployment rate is used as the endogenous variable, 0 otherwise
ENDY	Dummy, 1 if real GDP is used as the endogenous variable, 0 otherwise
LEVEL	Dummy, 1 if the model is written with the levels of the variables, 0 otherwise
DELTA	Dummy, 1 if the model is written with first differences of the variables, 0 otherwise
FILTLT	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with a linear trend, 0 otherwise
FILTHP	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with a HP filter, 0 otherwise
FILTBK	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with a Baxter King filter, 0 otherwise
FILTBN	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with a Beveridge Nelson filter, 0 otherwise
FILTUC	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with unobserved component models, 0 otherwise
FILTMOD	Dummy, 1 if the equilibrium paths of GDP and unemployment are estimated with specific models, 0 otherwise
YEAR	Publication year
YEAR2	Variable YEAR squared

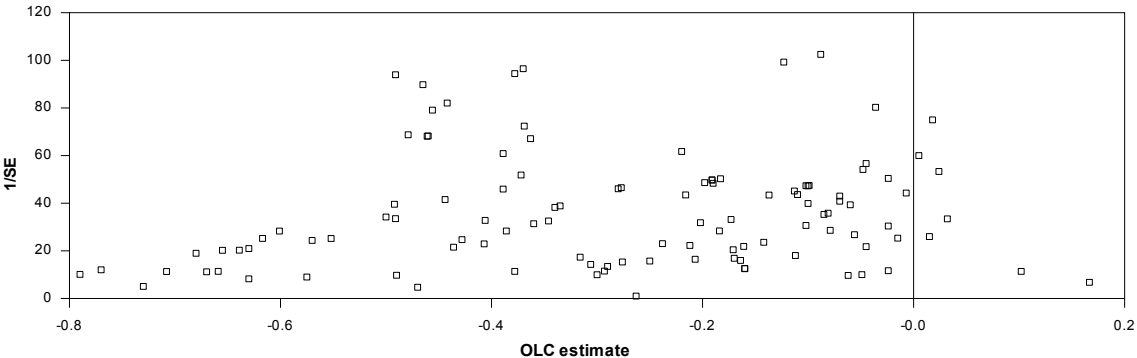
Regarding equation characteristics, as explained previously we first distinguish between models using unemployment as the endogenous variable (ENDU) and models using real output as the endogenous variable (ENDY). We then distinguish between static (MODSTA) and dynamic models (MODDYN), between models including only one exogenous variable

(NOOTHEXO) and models including several additional exogenous variables (OTHEXO), and then between single equation models (NEQ1) and multi equations models (NEQN). As the empirical evaluation of potential output and natural unemployment are essential steps in the estimation of the OLC, we also tried to take into account the precise nature of the econometric procedure retained for estimating these two variables. We thus constructed separate dummies for distinguishing between a linear trend methodology (FILTLT), an HP filter (FILTHP), a Baxter-King filter (FILTBK), a Beveridge-Nelson procedure (FILTBN), an unobserved components model (FILTUC) or an explicit model such as a production function for potential output (FILTMOD). In order to investigate more deeply the influence of model characteristics, we also included separate dummies for distinguishing between models in levels (LEVEL) and models in first difference (DELTA).

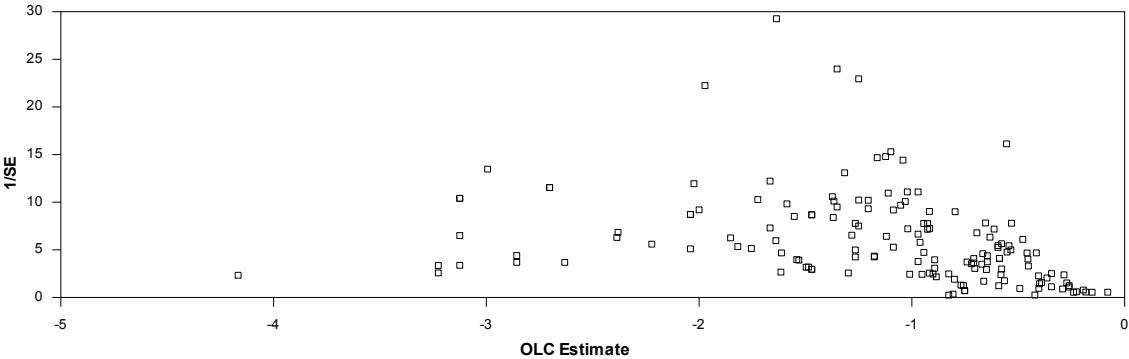
5. GRAPHICAL INVESTIGATION AND BIVARIATE TESTING FOR PUBLICATION BIAS AND TRUE EMPIRICAL EFFECT

As it is now common in applied MRA, we start by investigating the presence of type I publication bias by using the funnel plot technique. Figure 2a and 2b display the funnel plots for the unemployment sub-set and the real output sub-set, respectively. As a measure of precision, we use the inverse of the standard deviation of point estimates, which is plotted on the vertical axis; estimates of the OLC are plotted on the horizontal axis.

Insert Figure 2a near here. Caption: Funnel plot (unemployment sub-set)



Insert Figure 2b near here. Caption: Funnel plot (real output sub-set)



There are no positive estimates in the real output sub-set and only seven positive estimates in the unemployment subsample so that the plot is clearly outweighed on the left side in both cases. This asymmetry is strongly suggestive of publication bias. Even though macroeconomic theory generally leads to the prediction of a negative OLC, an unbiased set of empirical evidence on the OLC would be consistent with a symmetric distribution of estimated OLC around a negative mean. For the unemployment sub-set, visual inspection suggests a somewhat bimodal distribution of estimates; the mean of the two most precisely estimated values places the top portion of the funnel around -0.10, although the average of the top five points on the chart is substantially larger in magnitude, at around -0.3. In the case of the real output sub-set, the top portion of the funnel is close to -1.63 and the average of the top five points on the graph equals -1.35. These top values are quite far from the average of all the estimates (larger by 54% in the case of the unemployment sub-set and lower by 98% in the case of the real output subsample). Although there is a very high probability that the OLC is in fact negative, the potential magnitudes of the bias show that simple summaries of this literature may lead to a biased evaluation of the true size of the OLC.

As visual inspection of the funnel plots can be misleading and vulnerable to subjective interpretation, the funnel graphs are now supplemented with the FAT performed using Equation (5). Table 3 summarizes FAT results for the same samples as discussed before.

Insert Table 3 near here. Caption: Tests of type I publication bias and the true effect

		Dependent variable = <i>t</i> -statistic on the OL coefficient					
		OLS estimator			IRLS estimator		
	Obs.	β (bias)	α (precision effect)	R^2	β (bias)	α (precision effect)	R^2
Output sub-set	157	-2.060 (-5.22)***	-0.606 (-11.77)***	0.51	-1.970 (-6.53)***	-0.593 (-11.41)***	0.47
Unemployment sub-set	112	0.171 (0.12)	-0.265 (-8.39)***	0.39	-0.125 (-0.06)	-0.253 (-3.11)***	0.39

Empirical results obtained with the sub set of studies using some measure of real output as the dependent variable are presented in the row labeled “Output sub-set”, and empirical results obtained with the sub set of studies using some measure of unemployment as the dependent variable are presented in the row labeled “Unemployment sub-set”. Values of the *t*-statistics are given in parentheses. ***indicates significance at the level of 1%.

Before performing the FAT tests on each sub-set separately, we start by testing for the null that the data don’t need to be split into these two sub-sets. In order to do so, we merge the two subsamples then perform an OLS-estimation of equation (5) with the whole sample. We then perform a Chow test for the selected null hypothesis. The test produces an F statistic of 13.594 with an associated p value of 0.000 which clearly confirms the rejection of the null. As a result, the remaining part of the paper will in the main focus on these two sub-sets separately.

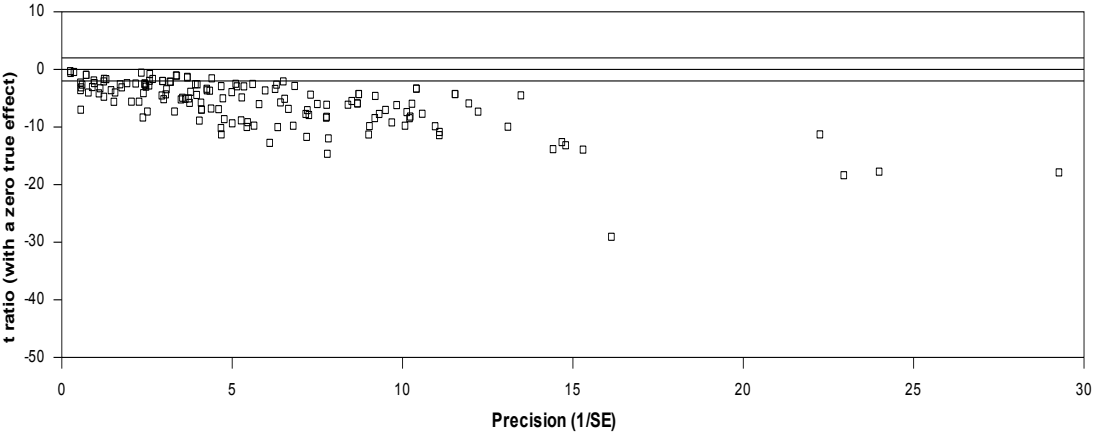
We now consider the sign and significance of publication bias for each of the two sub-sets.³ First consider the sub-set of studies with real output as the dependent variable (denoted “output sub-set” in Table 3). Here, the estimated sign of β suggests that the direction of a publication bias is negative. Moreover, using either OLS or IRLS estimator, the FAT test shows that the β coefficient (intercept term) is highly significant, so that the null of no type I publication bias is strongly rejected. Also note that not only is the β coefficient negative, but its size is larger than 2 in absolute value (or nearly 2 in the case of the IRLS estimator), which might be considered as an indication of a “severe selectivity” effect according to Doucouliagos-Stanley (2008).

³ For the combined (whole) set of studies, the estimated bias is negative.

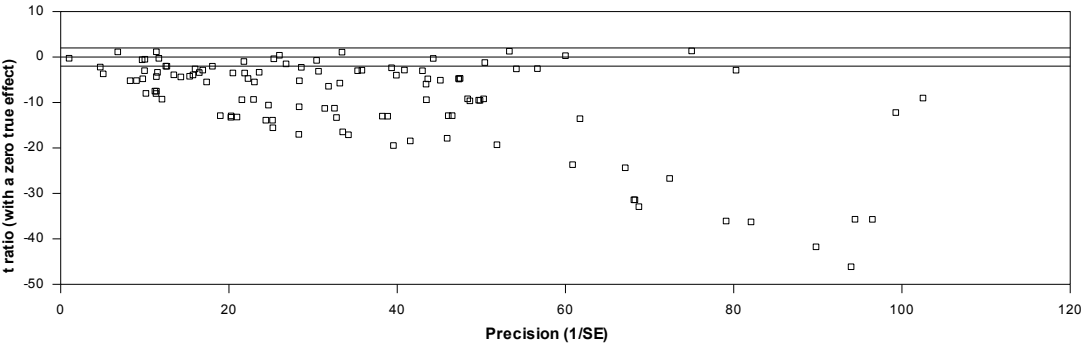
The story is different for the case of the sub-set of studies with the unemployment rate as dependent variable (denoted “Unemployment sub-set” in Table 3). In this case, the β coefficient is not significant with both OLS and IRLS estimators, so that the hypothesis of no type I publication bias is not rejected in this sub set.

Hence we find that a type I bias is present only in the sub set of papers estimating the Okun’s Law coefficient with empirical models using real output as the dependent variable. The difference between studies using real output as the endogenous variable and studies using unemployment rate as the endogenous variable is an important finding: while the first group of papers seems to be plagued by publication bias, the null hypothesis that the second group is not affected by this problem cannot be rejected at the usual confidence level.

Insert Figure 3a near here. Caption: Galbraith plot for the output sub-set



Insert Figure 3b near here. Caption: Galbraith plot for the unemployment sub-set



We now turn to type II bias, and begin by examining the Galbraith plots shown in Figure 3a and 3b for the output sub-set and the unemployment subsample respectively (the horizontal lines are the +2 and -2 limits for the t-statistics). The reported t-statistics exhibit both a wide variation and an apparent tendency to decline with rising precision. This visual examination of the Galbraith plots can be complemented by the use of z-type tests on the proportion of significant t-statistics. Table 4 reports the results of these z-tests.

Insert Table 4 near here. Caption: Tests of type II publication bias

	Proportion of Significant t-stat ^(a)	Z	P.value	Assumed True Effect
Endogenous : Real output	84%	41.50	0.00	0.00
	60%	30.66	0.00	-1.60 ^(b)
Endogenous : Unemployment	76%	38.80	0.00	0.00
	65%	34.95	0.00	-0.275 ^(b)

(a) Significance at the 5% confidence level

(b) True effect evaluated from the top 10% of the corresponding funnel graph

As can be seen in the Galbraith plots for the output sub-set and the unemployment subsample, type II biases seem to be present in both of these two sub samples. Assuming that there is no underlying true effect (TE = 0), only 5% of the studies should report t-statistics larger than 2. However, the proportions of studies reporting t-statistics exceeding 2 are close to 84% and 76% respectively and the null hypothesis that the proportion of significant t-statistic is equal to 5% is systematically rejected when the TE is taken to be zero ($z = 41.50$ with $p < 0.0000$ for the output sub-set and $z = 38.80$ with $p < 0.0000$ for the unemployment sub-set). Moreover, implementing the tests for a value of the TE evaluated from the top 10% of the

corresponding funnel graphs, the null hypothesis that the proportion of significant t-statistic is equal to 5% is again strongly rejected ($z = 30.66$ with $p < 0.0000$ for the output sub-set and $TE = -1.601$ and $z = 34.95$ with $p < 0.0000$ for the unemployment sub-set and $TE = -0.275$).

While studies using real output as the endogenous variable and studies using unemployment rate as the endogenous variable exhibited different results with respect to the null hypothesis of no type I publication bias, the null of no type II bias is now rejected for both sub samples (and also for the combined whole sample as it happens). In the literature on the OLC, this excess variation may thus reflect selection for statistically significant results.

Whereas the detection of the presence of publication bias is a necessary step in analyzing the literature, a more important question concerns whether there is an underlying true effect, irrespective of publication selection. As suggested by Stanley (2008), Equation (5) may also be used to test for an authentic empirical effect beyond publication bias. Empirical results of performing the PET on the slope coefficient α of equation (5) highlight the following points.

Using the α (precision effect) point estimates and t statistics reported in Table 3, the 95% confidence intervals reported by PET for the unemployment rate sub-set are: [-0.33 ; -0.20] with OLS and [-0.41 ; -0.09] with IRLS. In the case of the output sub-set, empirical estimates of the TE are much larger (in absolute values) since they vary from [-0.72 ; -0.52] with OLS to [-0.70 ; -0.50] with IRLS.

Aside from the evident sensitivity of results to the estimation procedure, the TE obtained for the OLC appears to be systematically larger (in absolute value) for the output sub-set than for the unemployment sub-set. Empirical models aimed at estimating the OLC by using models specified with real output as the dependent variable thus seem to lead to large estimators of the sensitivity of unemployment movements to real output fluctuations.

6. MULTIVARIATE META-REGRESSION ANALYSIS

To implement the multivariate MRA, we estimate equation (6) first for the full set of 269 estimates, and then separately for each sub-set of those estimates, where the partition is based

on choice of endogenous (dependent) variable. Each regression initially includes all the dummy explanatory variables listed in Table 2, other than those which have to be omitted so as to avoid linear dependence (in which case the constant term represents the effects of the omitted dummies). In this paper, the omitted dummies are SAMPTS, FREQY, COUNT, COUNTDED, MODSTA, NOOTHEXO, NEQ1, and DELTA.

Each model is first estimated with OLS. Insignificant variables are then excluded with a stepwise procedure involving both specific to general (or forward) and general to specific (or backward) selection steps to specify the finally estimated model. More precisely, variables are added to the model sequentially until no variable not yet in the model would, when added, have a t-statistic with a p value smaller than 0.05. Each time a variable is added to the model, variables with the lowest t-statistics are deleted until all remaining variables have a p value smaller than 0.05.

A robustness check was then performed by re-estimating the finally retained model with the iteratively re-weighted least squares method (IRLS) procedure. Meta-explanatory variables that appear as significant with both OLS and IRLS estimation of the finally selected model can be considered as the most influential effects on the value of the OLC. Lastly, in order to take into account the fact that the so-called “economics research cycle” (Havranek, 2010) may influence the size of the OLC, the year of publication (YEAR) and its square (YEAR2) are also added to the list of the finally selected significant variables. According to the economics research cycle hypothesis, when pioneering empirical results are published they are often quickly confirmed by other publications exhibiting highly significant estimates. After that, publishing skeptical results or empirical results that diverge with initial results may become preferable for editors in order to feed the controversies. A positive coefficient associated with the variable YEAR and a negative coefficient associated with YEAR2 (with joint significance) may indicate that the economics research cycle hypothesis is consistent with the data at hand in fully specified models. Empirical results are reported in Table 5.

In order to obtain more information about the influence of the endogenous variable on the OLC estimates, equation (6) is first estimated for the whole set of 269 OLC estimates, with the model including the full set of explanatory variables. Given our previous finding in Section 4, we are aware that this pooling process (stacking the effect of GDP on unemployment and the inverse of the effect of unemployment on GDP) is likely to be invalid.

But this is precisely why we do carry out this step so that here, in a more general multivariate context, the influence of endogenous variable (either GDP or unemployment) can be statistically tested for.

Of particular interest in this exercise is the role played by the dummy variable ENDY (which equals 1 if real GDP is used as the endogenous variable and 0 otherwise). In this case, the constant term captures the influence of omitted variables for the sub-set of models with unemployment rate as the endogenous variable and the coefficient associated with the dummy ENDY, where it is non-zero and significant, indicates by how much the OLC changes when moving from the unemployment sub-set to the real output sub-set.

This initial regression is presented in the first two columns of Table 5. The last four columns present the empirical results for the unemployment sub-set and the output sub-set respectively. For each pair of columns in the table, the first column in the pair lists unrestricted OLS regression results, while the second reports results from the IRLS estimator after applying the stepwise testing down procedure.

For the whole sample and each of the two sub-sets, F tests indicate that the estimated coefficients are jointly significant. However, in the unrestricted regressions, low values of t statistics indicate that some coefficients may be non-significant. This is confirmed by the stepwise testing down procedure.

For the ‘pooled regression’ using the full set of 269 OLC study estimates, the results of the multivariate analysis are consistent with the bivariate FAT model and also suggest the presence of a publication bias. Moreover, the estimated ‘true’ OLC equals -0.53 (with 95% confidence interval (-0.64, -0.42)) with the IRLS procedure. Note that in this multivariate analysis, the coefficient of the precision effect can be considered as a measure of the OLC for studies corresponding to the omitted dummies (i.e. studies using annual time series data for developed countries and single equation models specified as static relationships involving the first difference of unemployment rate as the dependent variable and the first difference of real output as the only dependent variable). As suggested by the value and significance of the coefficient associated with the moderator variable ENDY, studies using a model specified with output as the dependent variable tend to yield larger absolute values of the OLC (a positive sign means that the value of the OLC increases towards zero while a negative sign

means that the value of the OLC decreases away from zero). Moreover this effect appears to be highly significant, as revealed by the associated t-statistics. The use of real output instead of the unemployment rate as the dependent variable in the Okun's Law equation specification increases the absolute value of the OLC by 0.390 (on average). As the estimated Okun's Law coefficients in the sample are harmonized so as to represent the impact of output on unemployment, the coefficient on the unemployment variable retained for this group of studies is simply the inverse of the coefficient associated with unemployment (or employment) in the real output equation. As a consequence, the large negative values of the OLC estimated in this pooled group of studies may result from the fact that estimating some form of production function leads to an underestimation of the sensitivity of output to employment (or unemployment) because of simultaneity bias. The OLC calculated as the inverse of this coefficient is thus mechanically overestimated.

Insert Table 5 near here. Caption: Table 5: Multivariate meta regression analysis

	Whole set		Unemployment sub-set		Output sub-set	
	OLS	STEPWISE then IRLS	OLS	STEPWISE then IRLS	OLS	STEPWISE then IRLS
Constant	-240.41 (-2.01)	-194.45 (-3.00)	-286.50 (-0.72)		-274.87 (-3.24)	-327.92(-5.58)
Precision	-0.400 (-3.08)	-0.528 (-9.44)	-0.289 (-1.15)	-0.409 (-12.53)	-1.138 (-8.85)	-1.022 (-14.81)
SAMPPA	-0.261 (-1.74)	-0.174 (-1.80)			0.054 (0.64)	
FREQSQ	0.152 (1.37)	0.186 (4.38)	0.147 (0.72)	0.197 (4.55)	1.775 (5.36)	1.489 (11.86)
COUNTDING	0.188 (3.83)	0.225 (4.83)	0.139 (1.65)	0.205 (6.77)		
REG	0.334 (2.67)	0.293 (3.71)			0.183 (2.01)	0.192 (2.77)
MODDYN	0.117 (2.36)	0.145 (2.96)	0.008 (0.09)		1.379 (6.33)	1.107 (10.29)
OTHEXO	0.138 (2.16)	0.218 (5.54)	0.012 (0.10)		-0.764 (-4.34)	-0.614 (-5.22)
NEQN	-0.057 (-1.65)		-0.071 (-1.39)			
ENDY	-0.437 (-3.35)	-0.390 (-6.22)				
LEVEL	-0.124 (-1.71)		-0.253 (-1.89)	-0.211 (-5.85)	1.371 (5.33)	1.108 (8.473)
FILTLT	-0.153 (-1.09)		-0.055 (-0.11)		0.123 (0.85)	
FILTHP	-0.031 (-0.54)		-0.008 (-0.08)		0.134 (0.99)	
FILTBK	-0.160 (-1.00)		0.022 (0.05)		0.301 (1.77)	
FILTBN	-0.300 (-1.20)		-0.325 (-0.72)		0.106 (0.51)	
FILTUC	-0.019 (-0.16)		-0.012 (-0.05)		0.057 (0.32)	
FILTMOD	0.545 (0.88)					
AVGYEAR	0.120 (1.99)	0.097 (2.96)	0.143 (0.72)		0.138 (3.22)	0.164 (5.56)
R2	0.65	0.61	0.62	0.57	0.80	0.79
F-test (P. val.)	0.000	0.000	12.43 (0.00)	0.000	42.95 (0.00)	71.30 (0.00)
Reset test (P.val.)	0.061 (0.80)	0.024 (0.87)	0.003 (0.95)	0.936 (0.33)	2.097 (0.15)	0.557 (0.46)

For each estimated coefficient, the corresponding t-statistic is indicated in parentheses. The F-statistic tests the null hypothesis that independent variables are jointly equal to zero. The Ramsey Reset test corresponds to the null hypothesis of no omitted variable (linear functional form).

When splitting the whole sample so as to analyze separately the group of studies involving an Okun's Law model with unemployment rate as the endogenous variable and the group of studies with real output as the endogenous variable, the multivariate models lead to empirical results for publication bias and authentic empirical effect which are fully consistent with those from bivariate MRA. Papers with real output as the endogenous variable are affected by negative publication bias while no publication bias appeared as statistically significant in the case of papers with unemployment rate as the endogenous variable. Moreover, authentic empirical effects are significant in both groups of papers with a lower value (in absolute

terms) for the group of studies with unemployment rate as the endogenous variable. The precision effect equals -0.40 (with 95% confidence interval {-0.47, -0.34}) for the unemployment sub-set and -1.02 (with 95% confidence interval {-1.15, -0.88}) for the output sub-set.

For both sub-sets, it is important to note that the influence of the filtering procedure (such as the HP filter, or the Baxter King filter or Beveridge Nelson filter) is never significant after selection of the most influential moderator variables with the stepwise methodology. Finally, as in the case of the bivariate MRA, the hypothesis of an “economics research cycle” is systematically rejected at the 5% confidence level with both sub-sets ($F_{(2, 259)} = 0.327$ with p value = 0.722 for the unemployment rate sub-set and $F_{(2, 259)} = 0.960$ with p value = 0.385 for the real output sub-set).

Let us consider first results for the multivariate MRA using the ‘unemployment as endogenous variable’ sub-set. The null hypothesis of linear functional form (no omitted variables) for the estimated model is not rejected by the Ramsey RESET test. Empirical estimates of the magnitude of the OLC are affected by the frequencies of the data bases (FREQSQ: +), the development level of the countries (COUNTDING: +) and by whether the model specification is in terms of level or first difference of the variables (LEVEL: -). The higher the frequency of the data, the smaller the OLC (in absolute terms). Whereas adjustment may be rather rapid in some circumstances, it takes time for output variations to generate changes in the rate of unemployment. Quarterly or semestrial data bases may thus yield lower estimated OLC values. Other things equal, the estimated OLC is also lower (in absolute terms) when the data base includes only non OECD countries. One might conjecture, although we have no evidence for this here, that this may be explained by the dependence of the magnitude of the OLC on labour market institutions, the ease of hiring and firing workers, labour mobility, migration possibilities, and the nature of economic shocks. Finally, specification of the Okun’s Law model in levels (LEVEL=1) systematically leads to higher estimated OLC values (in absolute terms). One plausible explanation for this finding is that models estimated in levels (without filtering the data so as to exclude potential output or natural unemployment) will capture the total cumulated or long run effect of the exogenous variable on the endogenous variable. The corresponding estimates of the OLC may thus be expected to be larger with this kind of model.

We now consider results for the multivariate MRA using the ‘output as endogenous variable’ sub-set. The overall fit is quite high for a meta regression and the null hypothesis of linear functional form is again non-rejected by the RESET test. The last two columns of Table 5 show that empirical estimates of the OLC are smaller (in absolute value) when using semestrial or quarterly data rather than when using annual data⁴ (FREXSQ: +), and when using regional data instead of national data (REG: +).

The results in the last two columns of Table 5 show positive coefficients on the dummy variables picking out whether the specification used is that of a dynamic model of the Okun’s Law involving lags of the measure of unemployment and/or real output (MODDYN: +), and when the model specification is in terms of the levels of the variables (LEVEL: +). But we must take care in interpreting these two positive coefficient signs, particularly given that the positive coefficient on LEVEL in this regression appears to contradict the negative coefficient found on LEVEL in the MRA regression involving the unemployment sub-set. This apparent contradiction is easily resolved. In the case of models where **unemployment** is the endogenous variable, we reported in Table 5 that where a study used a regression in the levels of variables the OLC will be larger in absolute value; that is, the coefficient on LEVEL was negative. However, in the case of models where GDP is the endogenous variable, the same result will appear and the impact of unemployment on real output will be larger. But this will be revealed as a positive coefficient on the coefficient in Table 5 because we retain the **inverse of** the estimated OLC for models with output as the endogenous variable (so as to make them comparable to the OLC obtained when unemployment is endogenous).

The same reasoning applies to the coefficient attached to the variables MODDYN as it does to that attached to the variable LEVEL. They are both reported as positive (and of the same order) in Table 5. Hence, the coefficient on MODDYN implies that, for the case of studies using output as endogenous variable, the OLC will be larger in absolute value where models are estimated with dynamic regressions (including at least lags of the endogenous variables). Again, one might conjecture that this arises because such models will capture the total cumulated or long run effect of the exogenous variable on the endogenous variable.

Finally, one can see from the final two columns of Table 5 that a more recent data base also seems to lead to smaller values (in absolute values) of the OLC (AVGYEAR : +). In contrast,

⁴ This result that was also found in the sub-set using unemployment as endogenous variable.

the estimated impact on unemployment of output is larger (in absolute terms) when extra exogenous variables are added to the regression model (OTHEXO: -).

These results suggest the following. First, studies that use regional data instead of macroeconomic data are more likely to report smaller values (in absolute terms) of the OLC. This lower sensitivity of unemployment rate to regional output variations may be due to the fact that asymmetric regional output shocks are partly dampened by local or regional policy adjustments. Another possibility might be that regional labour market disequilibrium is partly cancelled by real wage variations and labour mobility so that the regulation doesn't systematically occur through variations in the number of unemployed persons. Secondly, the absolute value of the OLC tends to be smaller (in absolute terms) in studies using a dynamic model instead of a static one. Dynamic models incorporate lags of the endogenous variable and may also include lags of the exogenous variables as in the traditional autoregressive distributed lag (ARDL) model. Even with a limited number of lags, this kind of model may capture the total cumulated effect of real output variations on unemployment. This total cumulated effect of real output on unemployment may thus be expected to be lower than the impact effect evaluated with a static model if disequilibria of the labour market tend to vanish progressively over time. However, this interpretation has to be advanced with care because the retained sample does not allow us to investigate the context of complex dynamic effects such as threshold effects or nonlinear effects over time.

CONCLUSION

In this paper, we have been searching for the value of an underlying non observable parameter (a 'true effect'). However, in the real world, the observed value of the parameter or the estimated value of the parameter can be different from this underlying true value because of the characteristics of the country under examination, and of many other things such as data periodicity, the filtering procedure, and so on. It is these kinds of factors which can help one to understand and explain the large degree of heterogeneity of the Okun's Law coefficient in the associated empirical literature.

We selected a sample of 269 estimates of the Okun's Law coefficient from the literature to uncover the reasons for the differences in empirical results across studies and to estimate the 'true' OLC. On the basis of prior analysis suggesting the inappropriateness of pooling, we

then implemented a meta regression analysis on each of two sub-sets of studies: the group using some measure of unemployment as the dependent variable and the group employing a production function version of the Okun's Law with some measure of output as dependent variable.

While there is evidence of type II publication bias in both sub-sets, a type I bias is present only among the papers using a measure of output as the dependent variable. Moreover, taking into account those biases, the estimated true OLCs are significantly larger (in absolute value) with models using output as the dependent variable: (-0.61 instead of -0.25 with a bivariate MRA and -1.02 instead of -0.40 with a multivariate MRA). Our results clearly show that one of the primary sources of heterogeneity that can be identified in this literature is between studies which investigate the Okun's Law coefficient with a model including some measure of unemployment as the dependent variable and those that focus on a model involving some measure of output as the endogenous variable.

Thus, model specification is an important source of heterogeneity in this literature, and it may be reasonable to argue that there are two underlying 'true values' for the OLC depending on the choice of dependent variable. Selecting some measure of output as endogenous variable might amount to estimating a form of production function indicating the long-run impact of employment on real output. In contrast, when estimating the OLC with a model in which some measure of the unemployment rate is treated as the endogenous variable, such a specification seems adequate to capture the short run impact of aggregate demand movements on unemployment variations.

But of course choice of dependent variable is not the only source of heterogeneity. Among other possible sources of heterogeneity, we found the dynamic specification of the model, the frequency of the data, the degree of development of the countries and the choice between regional data and national data to be particularly important. To help interpret our results, let us consider characteristics of the zone or country in question, including the degree of development of the region or country. To capture (and control for) such factors, our multivariate MRA models included exogenous dummy variables to pick out whether a study only data base comprised only developed countries (or only developing countries) and whether a study data base only included countries (or only included regions). In doing so, we implicitly assume that the Okun's Law coefficient can be different from the true value because of two important

characteristics of the country under examination: the degree of development of the country or zone; and the degree of exogeneity of wages and the degree of labour mobility (through the dummies REG and COUNT).⁵ Moreover, including different countries will not bias our OLC estimates if the chosen dummies capture the main influence of the characteristics of the countries on the OLC. Thus, if one wished to identify the particular value of the Okun's Law relationship for a given country, one should not use the estimated 'true value' of the OLC, but rather use the value implied by our estimates for that country; that is, the value which takes into account the characteristics of this country.

Now we turn to what our results tell us about the true value of the OLC. After eliminating the influence of the main characteristics of each country (the previously mentioned dummies), the influence of the characteristics of the data bases and the characteristics of the econometric procedures, the fundamental true value of the Okun's Law coefficients are -0.61 and -1.02 (depending on the endogenous variables : unemployment or GDP). We cannot use these values for a given country but we can say that the real value of the correlation between unemployment and GDP movements should be close to -0.61 and -1.02, on average and across countries and regions.

Christophe: Should we be stronger here and argue that a preference should be given to the value found from studies using unemployment as dependent variable, as it does not have the problems we identified above (simultaneity in the production function approach, Type 1 bias in models using output as dependent variable)? If we could express such a preference, it would quash the potential criticism: should one use 0.61 or 1.02.

⁵ In the case of a region, wages can be assumed to be more or less exogenous and there is much more mobility than for a country as a whole.

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