Vol. 16(2), pp. 16-27, April-June 2024
DOI: 10.5897/JEIF2024.1215
Article Number: F6CA79372204
ISSN 2006-9812

http://www.academicjournals.org/JEIF

ACADEMIC JOURNALS
expand your knowledge

Journal of Economics and International Finance

Full Length Research Paper

Okun's law using structural change with threshold approach: Empirical evidence from the Democratic Republic of Congo (DRC)

Morisho Mwanabingo Nene[1,2]* and Minane Mpore Matthieu[2]

[1]Faculty of Economics and Management, Catholic University of Bukavu (UCB), DR Congo.
[2]Researcher, Pole Institute, Goma, DR Congo.

Received 7 February, 2024; Accepted 20 March, 2024

This paper employs the structural change with threshold approach to empirically verify Okun's law in the DRC. Utilizing quarterly data, the findings robustly support the existence of Okun's law in the DRC, albeit with a coefficient lower than that originally proposed by Okun. Moreover, the results reveal that the Okun coefficient in the DRC fluctuates significantly over time, irrespective of the economy's recessionary or expansionary phase. Based on these findings, it is imperative to diversify production across all sectors of the economy and enhance the business climate to ensure that economic growth translates into a notable reduction in the unemployment rate. Additionally, improving the education and skills of the labor force emerges as another crucial factor in this regard.

Key words: Okun's law, structural change with threshold, Democratic Republic of Congo (DRC).

INTRODUCTION

Alongside the Phillips curve, the inverse relationship between unemployment and output stands as one of the most stable macroeconomic relationships. This relationship, referred to as 'Okun's Law', suggests that in the absence of a productivity shock, an increase in output levels—such as those resulting from increased aggregate demand—will prompt firms to hire more workers to meet the expressed demand and consequently reduce the unemployment rate (Petkov, 2008). This law is not only of empirical interest to economists but also holds theoretical significance. When combined with the Phillips curve, the unemployment-output relationship forms the aggregate supply curve (Ball et al., 2016; Silvapulle et al., 2004). Furthermore, this relationship carries implications for defining macroeconomic policies, particularly in determining the desired or optimal growth rate (Gaëtan, 2014; Butkus and Seputiene, 2019).

While the basic relationship between unemployment and GDP has typically been modeled empirically within a linear framework, there are studies suggesting significant inconsistencies in the quantitative relationship between the unemployment rate and changes in output levels (Prachowny, 1993; Huang and Chang, 2005). For instance, Okun's (1962) estimates propose that a one-percentage-point increase in the unemployment rate correlates with approximately a 3% decrease in the

*Corresponding author. E-mail: morisho.mwanabiningo@ucbukavu.ac.cd.

growth rate of output. However, Prachowny (1993), considering factors such as weekly hours, induced labor supply, and productivity effects, suggests that a one-percentage-point reduction in the unemployment rate may only lead to a half-percentage-point increase in output levels.

Furceri (2012), employing static and dynamic panel regression techniques on Algeria, identifies a negative and significant relationship between the unemployment rate and GDP, yet obtains a notably low Okun coefficient of 0.05. Similarly, in a study comparing Okun's law across advanced and developing countries, Ball et al. (2019) find that, on average, the Okun coefficient is about half as large in developing countries as it is in advanced ones.

Moreover, in addition to disparities in the linear relationship between the unemployment rate and output, prior studies reveal asymmetry and temporal instability in this relationship. For example, Moosa (1997) examines the stability of the Okun coefficient across G7 countries using Chow and prediction error tests, discovering its instability over time. Alternatively, Huang (2003) analyzes the Okun relationship for the US and Canada utilizing the multiple structural change approach of Bai and Perron (1998, 2003), revealing instability in the unemployment-output relationship for both nations.

Furthermore, other studies suggest that the negative relationship between the cyclical component of GDP and the unemployment rate may exhibit non-linearity. Crespo-Cuaresma (2003), employing a threshold regression approach proposed by Hansen (2000), finds varying Okun coefficients across different phases of the production cycle, with high absolute values during recessions. Similarly, Huang and Chang (2005) combine the structural change methodology of Bai and Perron (1998, 2003) with Hansen's threshold regression method to scrutinize the validity of Okun's law in Canada, revealing temporal variability and phase-dependency of the Okun coefficient."

This revision breaks down the complex information into more manageable chunks, making it easier for readers to follow the argument and understand the nuances of the research findings.

The Democratic Republic of Congo (DRC), like many other countries worldwide, is continually affected by various shocks, both internal and external, which disrupt the relationship between certain macroeconomic variables. For instance, despite strong economic performance, there has been little to no reduction in the unemployment rate. To illustrate, data from the World Bank's development indicators show that the DRC achieved an average growth rate of 5.85% between 2010 and 2020, while over the same period, the unemployment rate rose by 27.6% (World Bank, 2020). In such an environment characterized by increasing macroeconomic instability, it becomes necessary to examine the verifiability of Okun's law. While a broad economic literature has extensively evaluated the validity of Okun's law in various economies worldwide, scant attention has been paid to this subject concerning the DRC.

Furthermore, to our knowledge, existing works evaluating the Okun relationship for the DRC do not consider important methodological aspects such as time instability and the non-linearity of the Okun coefficient, despite the significance of these aspects in formulating macroeconomic policies. This paper addresses both the instability and non-linearity issues in the data to study the validity of Okun's law in the DRC, using quarterly data from 1991Q1 to 2021Q4. Specifically, it assesses the existence of one or more breakpoints in the data over time using the procedure developed by Bai and Perron (2003). Subsequently, in each period identified in the first step, a threshold regression is estimated using the cyclical component of GDP as the threshold variable.

The motivation behind this paper is twofold. Firstly, aligning with the common perception that labor market behaviors in developing countries mainly reflect structural factors rather than short-run cyclical fluctuations (Ball et al., 2019), this paper proposes policy implications for the country to achieve integrated growth and improve the responsiveness of unemployment to output. Secondly, as the DRC has a large and growing share of the unemployed, understanding the drivers of unemployment deeply is of great importance. The rest of the paper is organized as follows: Section 2 presents the empirical literature review; Section 3 outlines the methodological approach; Section 4 summarizes the results of the analyses, and Section 5 concludes.

EMPIRICAL LITERATURE REVIEW

Since Okun's seminal work in 1962, numerous studies have focused on empirically evaluating the relationship between unemployment and output. These studies delve deeply into the Okun relationship, adapting it, making cross-country comparisons, or employing more sophisticated modern econometric techniques (Petkov, 2008). Despite different estimation methods yielding varying point estimators of the Okun coefficient, the relationship between unemployment and output has remained fairly robust (Ball et al., 2016). Several national-level studies have confirmed the validity of this relationship. Chamberlin (2011), for example, estimates the Okun relationship for Great Britain using ordinary least squares methods for both the first difference and output gap versions. His estimates demonstrate the validity of Okun's law in Great Britain for both versions. Similarly, using an Autoregressive Distributed Lag (ARDL) model, Lamzihri and Kamli (2021) empirically verify Okun's law in France, Italy, Spain, Morocco, Tunisia, Egypt, and South Africa over the period 1991-2020. Their results reveal a negative and significant impact of real GDP variation on the unemployment rate in both the short and long term across all these countries. Singh and Nurudeen (2022) estimate Okun's law for

China, utilizing both ordinary least squares and generalized method of moments (GMM) methods between 1991 and 2021, with their results indicating its validity for China. Balibwanabo and Tedika (2011) also find that Okun's law applies to the Democratic Republic of Congo, and similar results have been verified for several other African countries (Karim and Aomar, 2016) and Latin America (Pizzo, 2019). Despite the robustness of the relationship between output and unemployment at the national level, estimates of the latter across several countries suggest considerable variation across regions. Stephan (2014) argues that, to date, there is no definitive value for the Okun coefficient, even though theoretical and empirical strategies are gaining ground steadily. For instance, while Okun's (1962) estimates suggest that increasing the unemployment rate by one percentage point is accompanied by a 3% fall in the growth rate of output, Prachowny (1993), considering weekly hours, induced labor supply, and productivity effects, finds that a reduction in the unemployment rate of one percentage point could lead to an increase in output level of only about half a percentage point. Lee (2000) assesses the robustness of Okun's Law using post-war data for 16 OECD countries, finding statistical validity for most countries but with coefficients varying significantly. Furceri (2012), employing static and dynamic panel regression techniques on Algeria, finds a negative and significant relationship between the unemployment rate and GDP, with a very low Okun coefficient of 0.05. More recently, in a sample of 28 articles published between 1989 and 2009 on Okun's law, Gaëtan (2014), utilizing meta-analysis, identifies 269 Okun coefficients ranging between -3.22 and 0.17. Micallef (2017), using a first difference model in Malta, finds an Okun coefficient of 0.097, which he considers relatively low compared to other European countries.

Several of these studies attribute regional differences in the Okun coefficient to disparities in labor market institution regulations, changes in productivity and population growth, or economy-specific characteristics. However, as noted by Ball et al. (2016), most of these studies do not analyze these factors comprehensively in estimating the Okun coefficient. Some research is interested in analyzing the instability of the output-unemployment relationship over time. While some conclude that this relationship is characterized by instability over time, others find it stable.

Moosa (1997), for instance, examines the stability of the Okun coefficient for G7 countries using a Chow test and a prediction error test, revealing its instability over time. In France, Blanchard and Cohen (2007) demonstrate a positive change in the Okun coefficient, showing it increased from 0.17 in the 1960s and 1970s to 0.40 from 1981 to 2000. Huang (2003) analyzes the Okun relationship for the US and Canada using the multiple structural change approach by Bai and Perron (1998, 2003), indicating instability in the unemployment-output relationship for these two countries.

Conversely, Michail (2015) examines the stability of the Okun coefficient in the United States using a GARCH (General Autoregressive Conditional Heteroskedasticity) model and finds the unemployment-output relationship to be very stable over time, regardless of the estimation technique used. Other studies suggest that the negative relationship between the cyclical component of GDP and unemployment rate can be asymmetric, with varying effects during economic expansions and recessions.

For instance, Crespo-Cuaresma (2003) finds different Okun coefficients depending on the phases of the production cycle, with higher values observed during recessions. Owyang and Sekhposyan (2012) find that high unemployment period are correlated with increased sensitivity of the unemployment rate to GDP fluctuations but also observe high instability in historical Okun coefficient estimates using a rolling window approach. Daly et al. (2014) find a low Okun coefficient for the United States during the great recession, attributing it to revisions in US interest rates.

Using a threshold regression approach combined with quantile regression, Huang and Wang (2017) verify Okun's law in the US, revealing non-linearity in unemployment rate distribution quartiles and greater resilience of unemployment shocks during recession periods. Similarly, Yahia (2018) examines the Okun relationship for Malta and suggests a more pronounced relationship between output and unemployment rate during recessions than expansions. Ahn et al. (2019), using a sample of developed and developing countries, find that the youth unemployment rate is more sensitive in expansions than recessions, a conclusion also supported by Butkus and Seputiene (2019) in the European Union countries.

The above-mentioned studies have merit in testing for the existence of non-linearity and instability in the Okun coefficient, representing a significant advancement. However, none of them addresses both the existence of asymmetry and instability in the unemployment-output relationship. In recent years, another strand of literature has emerged, analyzing both instability and non-linearity of the Okun coefficient. Building on this, Huang and Chang (2005) employ an approach combining the structural change methodology of Bai and Perron (1998, 2003) with the threshold regression methodology of Hansen (2000) to assess the validity of Okun's law in Canada. Apart from a negative production-unemployment relationship, they find that the Okun coefficient is not stable over time and varies according to phases of the production cycle, particularly with high absolute values observed during recessions.

This study adopts the approach of Huang and Chang (2005) to investigate the case of the Democratic Republic of Congo. While the relationship between unemployment and output is well-documented in the literature, it has not received much attention from researchers concerning the

Democratic Republic of Congo, especially regarding the examination of stability and non-linearity of the Okun coefficient. This study contributes to the literature by examining the validity of the Okun coefficient for the Democratic Republic of Congo, simultaneously testing for the presence of asymmetry and instability in the Okun coefficient.

METHODOLOGICAL APPROACH

Model specification

Two versions of the model are used as references in the literature for estimating the Okun coefficient: the first-difference version and the output gap version. In the first-difference version, the Okun relationship links the variation in the observed unemployment rate to that in real GDP. This equation takes the following form:

$$\Delta u_t = \delta^p + \gamma^p \Delta y_t + \epsilon_t \quad (1)$$

where u_t is the unemployment rate, y_t the real GNP and ϵ_t the error term? δ^p is the constant and γ^p is the Okun coefficient. This coefficient gives information on the range of variation in the unemployment rate when real GNP varies by one percentage point. The gap version of the Okun relationship can also be presented in the following form:

$$u_t - u_t^n = \gamma^g (y_t - y_t^n) + \epsilon_t \quad (2)$$

where u_t^n is the natural rate of unemployment and y_t^n the potential GNP? γ^g Measures how much cyclical unemployment varies when the deviation of output from its potential level varies by 1%. To estimate the Okun relationship, some studies use the first difference version (Micallef, 2017) while others use the output gap version (Huang and Chang, 2005; Marinkov and Geldenhuys, 2007) and others both versions (Chamberlin, 2011; Gaëtan, 2014).

Each method has its advantages and disadvantages. For instance, the difference version lacks an explicit measurement of the trend component and relies on purely statistical and simple calculations directly derived from empirical data without making assumptions. However, as noted by Ball et al. (2019), this simplicity comes at a cost, as implicit assumptions about the trend components end up being subsumed in the constant term and the error term.

In contrast, the output gap version, while harder to measure and subject to various transformation techniques leading to different interpretations, summarizes the intensity of economic activity. Additionally, it holds economic significance and provides meaningful insights for policy decisions on the labor market by indicating how far the economy is operating from its full capacity. A negative output gap signals higher unemployment, while a positive gap suggests higher employment (Majaski, 2021). Furthermore, it's been shown by some researchers that there exists a robust relationship between the output gap and unemployment dynamics (Vitek, 2010).

For this research, the output gap version is considered in the estimates due to the reasons mentioned above. Despite its widespread use, this version has limitations. Notably, as Knotek (2007) points out, the major difficulty lies in the fact that potential GDP and the natural rate of unemployment are not directly observable and must be constructed. This has led to the development of several filters in time series econometrics for computing the gap between output and its potential level and between unemployment and its natural level.

Two commonly used filters are the Hodrick-Prescott (HP) filter, favored for its ease of implementation, and the Baxter and King (BK) filter, which, unlike the HP filter, does not explicitly determine potential GDP and the natural rate of unemployment (Baxter and King, 1999). Instead, it isolates the cyclical series by eliminating the trend component and the irregular component while choosing frequencies adapted to the temporal definition of a cycle (Gaëtan, 2014).

In addition to these filters, there are more complex options such as the Christiano Fitzgerald filter (CF), the Beveridge and Nelson decomposition, and Harvey's model with unobserved components. For robustness, this study employs two filters: the Hodrick-Prescott filter and the Christiano Fitzgerald (CF) filter (Christiano and Fitzgerald, 1999).

According to Weber (1995), Moosa (1999) and Huang and Chang (2005), the relationship between the cyclical component of unemployment and the cyclical component of output can be written in the following stochastic form:

$$u_t^c = \beta y_t^c + \epsilon_t \quad (3)$$

where $u_t^c = u_t - u_t^t$ denotes the cyclical component of the unemployment rate (the change in the unemployment rate u_t relative to its natural level u_t^t); $y_t^c = y_t - y_t^t$ denotes the cyclical component of real GDP, y_t real GDP and y_t^t the trend in real GDP. The parameter β represents the Okun coefficient, which is assumed to be negative ($\beta < 0$). This coefficient measures the elasticity of the unemployment rate to the variation in the level of output. Finally, t represents time and ϵ_t a white noise.

Equation 3 suggests that the relationship between unemployment and output is totally static, which some authors such as Moosa (1999) consider implausible. Following Weber (1995) and Moosa (1999), this equation can be made dynamic using the Autoregressive Distributed Lag (ARDL) model[1] which follows:

$$u_t^c = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-1}^c + \sum_{i=0}^{p} \beta_i y_{t-i}^c + \varphi_t \quad (4)$$

Where p represents the optimal lag which can be determined by the Akaike Information Criterion (AIC) or the Schwartz Information Criterion (SIC). The short-run effect of the level of output on employment is measured by the coefficient β_0 while the long-run effect is measured by calculating a function of the coefficients as shown in equation 5.

$$\omega = \frac{\sum_{i=0}^{p} \beta_i}{1 - \sum_{i=1}^{p} \alpha_i} \quad (5)$$

Estimation method

Following the work of Okun (1962), a number of studies have focused on the empirical verification of the output-unemployment relationship. In general, these studies take into account elements that Okun did not consider in his estimates, such as instability and asymmetry (non-linearity). In addition, most of these studies attempt to show the tendency of the linear specification to produce erroneous results for certain economic series. Froot and Rogoff (1995) and Lothian and Taylor (1996) point out, for example, the inadequacy of traditional tests (unit root tests and cointegration tests) in the presence of non-linearity in the series studied. Also, as Harris and Silverstone (2001) suggest, it is important to test for the existence of instability and non-linearity in the unemployment-output relationship.

This study refers to the following model based on the structural

[1]As Huang and Chang (2005) point out, the use of the ARDL model makes it possible to correct for the presence of autocorrelation in the model.

change and threshold approach:

$$w_t = x_t'\theta + z_t'\delta_j^{i_j} + \varepsilon_t \quad (6)$$

for $j = 1,2,\dots,m+1$ and $i_j = 1,2$. In this model y_t is the dependent variable and x_t' and z_t' are vectors of explanatory variables of order $(px1)$ and $(qx1)$. θ and $\delta_j^{i_j}$ are vectors of the parameters to be estimated. Equation 6 is an example of a model with partial structural change where the structural change affects only $\delta_j^{i_j}$, with θ being estimated using the whole sample. This model is said to be pure when p is equal to 0. In this case, all the parameters of the vector $\delta_j^{i_j}$ are affected by the structural change. This equation makes it possible to have m breakpoints (structural changes) with $m+1$ regimes. Within each regime, there is a threshold y_t^c value of 0. Taking p to be 0 and redefining$w_t = u_t^c$, $z_t = (1, u_{t-1}^c, u_{t-2}^c, \dots, y_t^c, y_{t-1}^c, y_{t-2}^c, \dots)'$ and $\delta_j = (\alpha_{j0}, \alpha_{j1}, \alpha_{j2}, \dots, \beta_{j0}, \beta_{j1}, \beta_{j2}, \dots)'$the structural change approach with threshold applied to the Okun relationship can be presented as follows:

$$u_t^c = \begin{cases} z_t'\delta_1^- + \varepsilon_t & Si\ t \le T_1 \quad et \quad y_t^c < 0 \\ z_t'\delta_1^+ + \varepsilon_t & Si\ t \le T_1 \quad et \quad 0 > y_t^c \\ z_t'\delta_2^- + \varepsilon_t & Si\ T_1 \le t \le T_2 \quad et \quad y_t^c < 0 \\ z_t'\delta_2^+ + \varepsilon_t & Si\ T_1 \le t \le T_2 \quad et \quad 0 > y_t^c \\ & \vdots \\ z_t'\delta_m^- + \varepsilon_t & Si\ T_{n-1} \le t \le T_n \quad et \quad y_t^c < 0 \\ z_t'\delta_m^+ + \varepsilon_t & Si\ T_{n-1} \le t \le T_n \quad et \quad 0 > y_t^c \end{cases} \quad (7)$$

wher**e** u_t^c is the cyclical component of the unemployment rate, y_t^c the cyclical component of the economic growth rate, α_{ji} and β_{ji} the parameters to be estimated for each regime and ε_t the error term. The indices t and m represent the time and the number of breakpoints respectively. Assuming a threshold y_t^c of 0, two threshold regressions will be estimated within each regime: one for negative values and the other for positive values of the threshold variable (the cyclical component of the economic growth rate). This system of equations will be estimated sequentially. First, it will be examined whether it is affected by one or more breakpoints (structural change) using the procedure of Bai and Perron (2003). If so, within each regime, a threshold regression will be estimated with the value 0 as the threshold.

The Bai and Perron (2003) procedure generalises the Andrews (1993) test by allowing for several breakpoints in the data. Specifically, Bai and Perron (2003) use an ordinary least squares procedure to obtain the data and propose a dynamic programming algorithm to compute the estimators (Enders, 2015). The Bai and Perron (2003) algorithm proposes two different ways of selecting the number of breaks. Firstly, it estimates two Fisher-type tests, all based on the null hypothesis of no structural change against the alternative hypothesis of the presence of k breakpoints[2] , namely the Supremum test (Sup F test) and the double maximum tests (UD max and WD max). When the calculated value of these tests is greater than the critical value of Bai and Perron (2003) at the threshold used, generally 5%, or when the critical probability associated with this calculated value is less than the standard significance threshold of 5%, the alternative hypothesis of the presence of k breakpoints is accepted. Otherwise, the null hypothesis of no structural change cannot be rejected.

[2] Bai and Perron (2003) recommend using a trimming value of 15% and a maximum number of 5 breakpoints. Enders (2015) points out that this technique is important because it allows each segment separated by breakpoints to have enough observations to be properly estimated.

The second method of selecting the number of breakpoints consists of using a sequential test known as the $F(\ell+1|\ell), \ell = 1,2,3,\dots$. This test starts with the null hypothesis of no breaks against the alternative hypothesis of a single break. If this null hypothesis is rejected, the null hypothesis of a single break is tested against the alternative hypothesis of two breaks, and so on. The process continues until the test no longer rejects the null hypothesis of no further breaks. The method is sequential in the sense that the test for ℓ + 1 breaks takes the first ℓ breaks as given (Enders, 2015). According to Huang and Chang (2005), the results of the simulations would prefer that we first start with the UD max or WD max tests to test whether there is at least one breakpoint. If these two tests indicate such evidence, then the maximum number of breakpoints can be determined by sequentially examining the $F(\ell+1|\ell)$ tests. Also, Bai and Perron (1998) and Bai and Perron (2003) point out that this procedure leads to better results and recommend it in empirical applications. This is the procedure adopted in this study.

Data description

The data used in this study is taken from the World Bank's development indicators (World Bank, 2020). They relate to two variables: the unemployment rate (TotUnemp) and the GDP growth rate (GDPgrowth). These two variables are observed between 1991 and 2021. The choice of this period was dictated by the availability of data for the unemployment rate. The unemployment rate refers to the proportion of the working population that is unemployed but looking for work and available for work. The GDP growth rate represents the annual percentage rate of GDP growth at market prices based on constant local currencies. Aggregate data are based on constant 2010 US dollars. It is clear from the above that the data is only available for a period of 30 years. This period proves to be limited (due to few observations) for implementing the estimation method chosen for this study (the structural change with threshold approach). Although demanding in terms of sample size, this method is necessary for validating the Okun relationship in the DRC. This being the case, we calculate the quarterly values of these series following the example of Fortin et al. (2022). The literature on this subject includes several methods grouped into purely mathematical smoothing methods and correlation methods that use exogenous indicator variables to capture the business cycle information in the variable to be transformed in quarterly values. The method of Denton (1971) falls into the first category, while the methods of Chow and Lin (1971) and Ginsburgh (1973) fall into the second. Denton's method was applied in this research. After quarterly data analysis, a total of 124 observations were obtained (1991Q1 to 2021Q4).

RESULTS

This part presents the descriptive analyses of the relationship between the unemployment rate and the GDP growth rate, the estimates of the linear model and those of the structural change model with threshold.

Descriptive analyses of the relationship between the unemployment rate and the GDP growth rate

This part presents the analysis of the correlation coefficient and the graphical representation of the linear relationship between the cyclical components of the unemployment rate and the GDP growth rate. Table 1

Table 1. Correlation between the unemployment rate and the GDP growth rate.

	Hodrick-Prescott filter		Christiano-Fitzgerald filter	
Period	1991Q1-2021Q4		1991Q1-2021Q4	
	TotUnemp	P-value	TotUnemp	P-value
GDPgrowth	-0.2102	0.0207	-0.3885	0.0000
Period	1991Q1-2016Q3		1991Q1-2016Q4	
	TotUnemp	P-value	TotUnemp	P-value
GDPgrowth	-0.2666	0.0068	-0.3844	0.0001
Period	2016Q4-2021Q4		2017Q1-2021Q4	
	TotUnemp	P-value	TotUnemp	P-value
GDPgrowth	-0.3345	0.1615	-0.7862	0.0000

Source: based on World Bank data (2020).

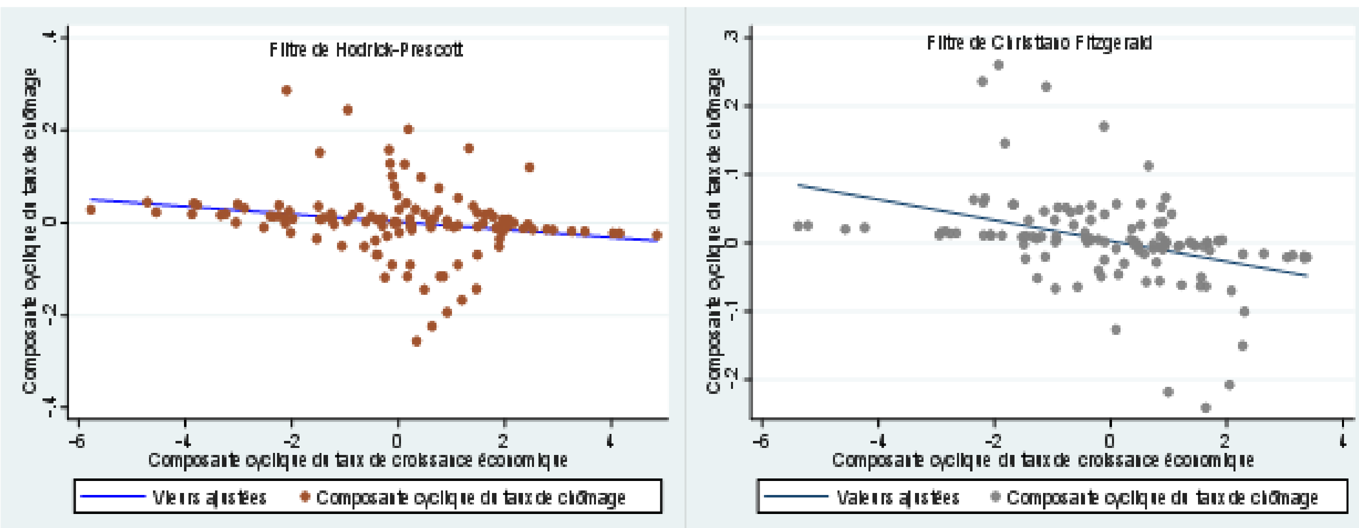

Figure 1. Graphical representation of the linear relationship between the cyclical components of the unemployment rate and the GDP growth rate from 1991: Q1 to 2021: Q4.

shows the results of the correlation analysis between the two variables over the entire study period (1991Q1-2021Q4) and two sub-periods (1991Q1-2016Q4 and 2017Q1-2021Q4)[3]. Although low, the correlation coefficient for the entire sample is negative (-0.2102 for the HP filter and -0.3885 for the CF filter) and significant (p-value= 0.0207 for the HP filter and 0.0000 for the CF filter) for both filters.

Calculating the correlation between the unemployment rate and the GDP growth rate in the two sub-periods yields interesting results: the correlation is more pronounced in the second period than in the first. For the pre-break period, it is -0.3345 (HP filter) and -0.7862 (CF filter), compared to -0.2666 (HP filter) and -0.3844 (CF filter) for the post-break period. The pronounced difference in correlations between the two sub-periods could primarily be attributed to the structural change in the data.

Beyond the correlation coefficient, Figure 1 illustrates a negative linear relationship between the unemployment rate and the GDP growth rate for both the Hodrick-Prescott and Christiano-Fitzgerald filters. Furthermore, the negative linear relationship between the two variables is nearly identical for both filters, although it tends to be more pronounced when the Christiano-Fitzgerald filter is applied. These results, combined with those of the correlation analysis, provide preliminary evidence supporting the empirical verification of Okun's law in the DRC.

[3] These two periods are separated, for each filter, by a breakpoint (2016Q3 for the Hodrick-Prescott filter and 2016Q4 for the Christiano-Fitzgerald filter) determined by the approach of Bai and Perron (2003). The results of the structural change tests are detailed below.

Table 2. Dynamic linear estimation of the Okun coefficient.

Coefficients	Hodrick-Prescott filter		Christiano-Fitzgerald filter	
	Jack-knife	Newey-West	Jack-knife	Newey-West
α_0	0.00105 (0.00255)	0.00105 (0.00378)	-0.000102 (0.00228)	-0.000102 (0.00365)
α_1	0.955*** (0.0731)	0.955*** (0.0553)	0.918*** (0.0645)	0.918*** (0.0659)
β_0	-0.0132*** (0.00315)	-0.0132*** (0.00478)	-0.0153*** (0.00381)	-0.0153** (0.00611)
β_1	0.0105*** (0.00261)	0.0105*** (0.00375)	0.0115*** (0.00308)	0.0115** (0.00475)
$\boldsymbol{\omega}$	-0.06	-0.06	-0.046	-0.046
R-squared	0.878		0.871	
F-stat	102.27***	126.19***	87.08***	73.23***

Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1.

The linear model

This part of the study presents the empirical results of the linear dynamic model as described in equation 4. The ARDL (1,1) model is selected as optimal because it minimizes the Akaike (AIC) and Schwartz information criteria (SIC). To ensure the robustness of the results, two equations were estimated: one with the data decomposed by the Hodrick-Prescott filter and the other with the datadecomposed by the Christiano-Fitzgerald filter. The results reported in Table 2 are estimated using the ordinary least squares method. For each equation, the standard errors are corrected for possible heteroscedasticity and autocorrelation using the Newey-West (1987) correction. Additionally, the Jack-knife variance-covariance matrix is applied. Recent studies indicate that estimates of the variance-covariance matrix using the Jack-knife method have properties that are particularly useful in practice: they are unbiased in small samples and provide better coverage rates for confidence intervals than other "robust" estimates (Bell and McCaffrey, 2002; Zeileis et al., 2020; Hansen, 2022). Furthermore, as the Jack-knife variance-covariance matrix is based on the re-estimation of sub-sample results, it is broadly similar to that obtained by the bootstrap method (Zeileis et al., 2020).

Table 2 presents the estimates of the dynamic linear relationship between the unemployment rate and the GDP growth rate. The calculated values of the Fisher statistic are significant at the 1% level (p-value < 0.001) for both filters (HP and CF) and for all equations, indicating overall significance of these models. Additionally, the coefficients of determination (0.878 for the HP filter and 0.871 for the CF filter) suggest that the explanatory variables in the estimated models account for 87% of the variance of the cyclical component of the unemployment rate. The overall significance and high explanatory power of the estimated models provide strong evidence that they fit the data well.

Examining the estimated coefficients, it is observed that, apart from the intercept α_0, which has a positive sign for the HP filter and a negative sign for the CF filter and is insignificant for all models, all other coefficients are significant at the 1% significance level and exhibit similar signs for both filters (HP and CF) and all estimation methods. The coefficient of β_1 is significant at the 5% level for the CF filter when the Newey-West correction is applied. Additionally, the signs of the coefficients are consistent, and their values are approximately equal. The coefficient α_1 is positive and takes values of 0.955 and 0.918 respectively for the HP filter and the CF filter. This indicates that when a shock to the unemployment rate occurs in one period, it is transmitted to the next period at 95.5 or 91.8%, respectively. In other words, the unemployment rate observed in a given quarter is also observed at 95.5 or 91.8% in the following quarter.

The short-term Okun coefficient, β_0, is negative for both filters (HP and CF) and for all the estimation methods used, with values of -0.0132 and -0.0153 respectively for the HP and CF filters. Additionally, calculated using Equation 5, the long-term Okun coefficient is -0.06 and -0.046 for the HP and CF filters respectively. These coefficients indicate that for the DRC, a variation in the GDP growth rate of one percentage point is accompanied by a decrease in the unemployment rate of between 0.0132% (HP filter) and 0.0153% (CF filter) in the short term, and between 0.06% (HP filter) and 0.046% (CF filter) in the long term. These results provide empirical evidence in support of the Okun relationship in the DRC. However, compared with the coefficients estimated by Okun (1962), Moosa (1997), Crespo-Cuaresma (2003), or even Huang and Chang (2005), the estimated coefficients are relatively low in magnitude.

Such results can be explained by several factors. In the short term, the low magnitude of the Okun coefficient could be attributed to low-quality growth driven primarily by a single sector, mining, which is capital-intensive but creates fewer jobs. Additionally, the structure of the Congolese labor market, characterized by a high degree of rigidity on the supply side and various frictions (such as the mismatch between education and the real needs of the labor market), may also contribute to the low magnitude of this coefficient. In the long term, demographic factors, particularly the growth of the active population, could play a decisive role in explaining the low sensitivity of the unemployment rate to variations in the GDP growth rate. In fact, in the long term, a faster growth in the active population compared to the number of jobs created can lead to a substantial pool of unemployed individuals that periodic job creation may struggle to reduce.

Furthermore, the coefficient of the cyclical component of the one-period lagged GDP growth rate is positive, with values of 0.0105 and 0.0115 respectively for the HP and CF filters. This indicates that an increase in the GDP growth rate of one percentage point in one period is accompanied by an increase in the unemployment rate of 0.0105 or 0.0115 in the following period.

Estimation of Okun's law using the structural change and threshold approach

This part of the study sets out to estimate the Okun relationship for the DRC using the structural change and threshold approach. We first determine the number of breakpoints and then present the estimation results.

Determining the number of breakpoints

The results of the Bai and Perron (2003) test are presented in Table 3. The determination of the number of breakpoints is done in two steps. First, as suggested by Huang and Chang (2005), the UD max and WD max tests are considered to determine whether there is at least one breakpoint in the data. Next, the sequential test

$F(\ell+1|\ell)$ is performed to determine the maximum number of breaks.

It can be noted that the UD max and WD max statistics give statistically significant values at the 1% threshold for both the Hodrick-Prescott filter and the Christiano-Fitzgerald filter, justifying that the data contains at least one breakpoint. Having already established the presence of at least one breakpoint in the data, it is then tested whether there are additional breakpoints using the sequential tests $F(\ell+1|\ell)$, l > 1. The results of all the sequential tests greater than 1 fail to reject the null hypothesis that there is no breakpoint of order greater than 1. Combined with the results of the UD max and WD max tests, they suggest that there is only one breakpoint in the data, regardless of the filter used.

The identified breakpoint is in the third quarter of 2016 (2016Q3) when the Hodrick-Prescott filter is applied and in the fourth quarter of 2016 (2016Q4) when the Christiano-Fitzgerald filter is applied. The confidence intervals are also very short for both filters (2016Q2 to 2016Q4 for the HP filter and 2016Q3 to 2017Q1 for the CF filter), indicating high accuracy of the estimates.

As a result, the sample that will be the subject of the estimates in the following lines is subdivided into two sub-periods separated by the identified breakpoint. The first, longer period contains 102 observations for the Hodrick-Prescott filter (1991Q1 to 2016Q3) and 103 observations for the Christiano-Fitzgerald filter (1991Q1 to 2016Q4). The second, shorter period contains 22 observations for the Hodrick-Prescott filter (2016Q4 to 2021Q4) and 21 observations for the Christiano-Fitzgerald filter (2017Q1 to 2021Q4).

The observed break in 2016 can be attributed to the fall in commodity prices on the international market during the year, particularly for minerals such as cobalt and copper, which significantly contribute to the country's economic growth. This external shock was further exacerbated by the political uncertainty that characterized the country from 2016 onwards, with implications on the productive apparatus and the state budget.

In addition to addressing the question of structural change, the second issue considered in the estimates is that of non-linearity. The methodology involves estimating a threshold regression within each regime identified by the structural change test. However, due to the limited number of observations in the second regime, asymmetry will only be assessed in the first regime, which has relatively more observations than the second. Consequently, the threshold regression, with 0 as the threshold, will only be estimated in the first period.

Estimation results

Based on the number of breakpoints determined by the multiple structural change test of Bai and Perron (2003), this section summarizes the estimates of the structural change model with a threshold. Firstly, the Okun relationship is evaluated between the two periods separated by the identified breakpoint. Secondly, a threshold regression is estimated only in the first period with the cyclical component of the GDP growth rate as

Table 3. Determining the number of breakpoints.

Tests*	Hodrick-Prescott	Cristiano-Fitzgerald
UD max	26.99***	67.78***
WD max	26.99***	67.78***
Sup F (1|0)	28.07***	76.18***
Sup F (2|1)	6.06	4.13
Sup F (3|2)	6.89	2.74
Sup F (4|3)	7.48	5.47
Number of break-ups	1	1
Breaking point	2016Q3	2016Q4
Lower IC	2016Q2	2016Q3
Superior IC	2016Q4	2017Q1

* The maximum number of breakpoints is set at 4 and the percentage fit at 15% for both filters. The number of breakpoints is chosen using the statistic $F(\ell+1|\ell), \ell = 1,2,3$ based on a significance level of 1%.
*** Significant at the 1% threshold.

Table 4. Estimation results for the structural change model with threshold.

Coef.	Hodrick-Prescott filter				Christiano-Fitzgerald filter			
	Period I: 1991Q1-2016Q3			Period II	Period I: 1991Q1-2016Q4			Period II
	Package	$y_t^c < 0$	$y_t^c > 0$		Package	$y_t^c < 0$	$y_t^c > 0$	
α_0	-0.000203	0.00891***	-0.00324	0.0344**	0.000305	0.00214	-0.00160	0.0177**
	(0.00114)	(0.00250)	(0.00332)	(0.0132)	(0.000986)	(0.00326)	(0.00179)	(0.00731)
α_1	0.972***	1.041***	0.927***	1.151***	0.944***	0.920***	0.976***	0.766***
	(0.0586)	(0.0665)	(0.0710)	(0.0760)	(0.0419)	(0.0699)	(0.0383)	(0.0843)
β_0	-0.00595***	-0.00271**	-0.00415**	-0.103***	-0.00585***	-0.00536***	-0.00451***	-0.0606***
	(0.000548)	(0.00111)	(0.00180)	(0.0142)	(0.000834)	(0.00158)	(0.00149)	(0.0148)
β_1	0.00478***	0.00583***	0.00321**	0.0896***	0.00523***	0.00537***	0.00500***	0.0200
	(0.000691)	(0.000989)	(0.00157)	(0.0179)	(0.000886)	(0.00130)	(0.00122)	(0.0188)
$\boldsymbol{\omega}$	-0.041	-0.0625	-0.0123	0.0722	-0.0111	0.000128	0.01914	-0.187
R-squared	0.943	0.969	0.944	0.948	0.903	0.846	0.959	0.973
F-Stat	208.25***	82.06***	97.61***	125.70***	504.87***	59.80***	275.11***	210.05***

Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1.

the threshold variable. All models are estimated using the ordinary least squares method. A Jack-Knife correction is applied to the variance-covariance matrix of the residuals. This choice is guided by the fact that this correction gives unbiased estimators in small samples (Bell and McCaffrey, 2002; Hansen, 2022; Zeileis et al., 2020), which is better suited to this section given that the data used are subdivided into sub-samples.

The results in Table 4 show that all the estimated equations are globally significant, irrespective of the periods considered and the filter applied to the data: all the values calculated for the Fisher test are significant at the 1% threshold. The results also give high coefficients of determination tending towards 1 for all the equations. This shows that, in all these equations, the explanatory variables considered account for approximately 100% of the variation in the cyclical component of the unemployment rate.

For the second regime, the results of the estimations, presented in the fourth column of Table 4, give significant coefficients whose signs coincide (except for the β_1 coefficient, which is not significant for the CF filter, and the long-term multiplier, whose sign alternates for the two filters). The intercept is positive and significant at the 5% threshold for both the data decomposed with the HP filter and the data decomposed with the CF filter. The intercept is 0.0344 (HP filter) and 0.0177 (CF filter) respectively.

Among the explanatory variables, the AR (1) coefficient is significant and positive for both filters (HP and CF). This coefficient, which measures the persistence of unemployment rate dynamics over time, is 1.151 and 0.766 respectively for the Hodrick-Prescott and Christiano Fitzgerald filters. Like the results of the linear method, this autoregressive coefficient is positive.

The Okun coefficient obtained is negative (-0.103) for the HP filter and significantly different from 0 (p-value<0.001). In absolute terms, it is much higher than that obtained in the linear estimations. The same observation is made for the CF filter. The lag of the cyclical component of the GDP growth rate, β_1 is positive for both filters but only statistically significant for the Hodrick-Prescott filter. This coefficient is higher in absolute value than that obtained in the linear estimates. Finally, the long-term multiplier is 0.0722 for the Hodrick-Prescott filter and -0.187 for the Christiano-Fitzgerald filter. These coefficients are higher in absolute value than those of the linear estimates and correspond to a large variation in the unemployment rate for a variation of one percentage point in the GDP growth rate.

Estimates are conducted in two stages for the first regime. Firstly, for the entire period without considering the effect of the threshold (the first column for each filter), and then taking into account the effect of the threshold (the second and third columns for each filter). Regarding the overall estimates, results indicate that except for the intercept, which is not significantly different from 0 and alternates in sign for the two filters (HP filter and CF filter), all other coefficients are statistically significant and exhibit consistent signs. Additionally, there are no substantial differences in the absolute values of these parameters between the Hodrick-Prescott and Christiano-Fitzgerald filters.

The AR(1) coefficient, which assesses the percentage impact of unemployment shocks from one period to another, displays a positive sign and takes values of 0.972 and 0.944 respectively for the HP filter and the CF filter. This value is lower than that obtained in the linear estimates and the post-break period. The Okun coefficient, β_0, is -0.00595 for the data filtered with the HP filter, which is lower than the estimation in the second period. Similar observations are made for the CF filter.

From these results, it can be concluded that the Okun coefficient was larger in absolute value after 2016, the year in which the structural change occurred, compared to the period between 1991 and 2016. The long-term coefficient is also negative for both filters (HP and CF), with values of -0.041 for the HP filter and -0.0111 for the Christiano-Fitzgerald filter.

After presenting the overall results for the first period, the threshold regression is estimated within this period. Following Crespo-Cuaresma (2003), the data for the first period are divided into two regimes: recession ($\boldsymbol{y_t^c} < \mathbf{0}$) and expansion ($\boldsymbol{y_t^c} > \mathbf{0}$). The results indicate that most estimated parameters are statistically significant at the 5 and 10% thresholds (except for the intercept, which is not significant in the expansion period for the Hodrick-Prescott filter).

Additionally, apart from the intercept and the long-term coefficient, all other coefficients have consistent signs. The AR(1) coefficient is positive and greater than 0.9 for all filters (HP and CF), whether in recession or expansion. This indicates that a shock in the unemployment rate observed in any period is more than 90% visible in the following period.

Furthermore, the results show that the AR(1) coefficient is higher during the recession period than during the expansion period for the Hodrick-Prescott filter. However, the opposite is observed for the Christiano-Fitzgerald filter.

The Okun coefficient is negative in both recessions and expansions for all filter used, suggesting that the Okun relationship is empirically evident in the DRC even in periods of recession and expansion.

For the Hodrick-Prescott filter, the Okun coefficient is higher in expansion periods than in recession periods, while the opposite is observed for the Christiano-Fitzgerald filter.

Moreover, the long-term Okun coefficient is positive for the Christiano-Fitzgerald filter in both recession and expansion periods. These results indicate that although the Okun relationship is empirically evident in the DRC during both expansion and recession, the unemployment rate is not differently affected by the GDP growth rate according to the phases of the economic cycle.

These findings differ from those obtained by Crespo-Cuaresma (2003) and Huang and Chang (2005), who found that unemployment is more sensitive to changes in the level of output during recessions than during expansions.

CONCLUSION AND IMPLICATIONS FOR ECONOMIC POLICY

This study provides an empirical verification of Okun's law in the DRC, considering two critical factors in time series analysis: structural change and asymmetry. The results robustly suggest that Okun's law is a stylized fact in the DRC. However, the Okun coefficient is relatively low compared to that obtained in Okun's seminal work. Furthermore, the results indicate that the Okun coefficient varies substantially over time but does not differ according to whether the economy is in recession or expansion.

These findings have significant implications for the implementation of macroeconomic policies. The notably low Okun coefficient signals the low quality of economic growth in the DRC, which fails to generate sufficient employment opportunities. The heavy reliance on the mining sector for economic growth, which cannot absorb the entire active population, contributes to the reduced sensitivity of the unemployment rate to changes in economic growth. Addressing this issue requires the development of policies aimed at diversifying economic activities, particularly by bolstering production in other sectors like agriculture. Achieving this objective necessitates improving the overall business climate within the country, enabling entrepreneurs to expand operations in alternative economic sectors and thereby create more job opportunities for the workforce. Additionally, investing in education and enhancing the skills of the labor force are crucial factors for fostering sustainable economic growth and reducing unemployment in the DRC.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Ahn JW, Chang MD, Kokku R, Watson P (2019). International Business Machines Corp, assignee. Blockchain for open scientific research. United States patent US 10,511,452. 2019 Dec 17.

Bai J, Perron P (1998). Estimating and Testing Linear Models with Multiple Structural Changes. Econometrica 66:47-78.

Bai J, Perron P (2003). Computation and Analysis of Multiple Structural Change Models. Journal of Applied Econometrics 18(1):1-22

Balibwanabo AM, Tedika OK (2011). Okun's law in the Democratic Republic of Congo: Empirical evidence. Revue Congolaise D'économie 6(1):19-41.

Ball L, Furceri D, Leigh D, Loungani P (2016). Does One Law Fit All? Cross-Country Evidence on Okun's Law. IMF, Vanderbilt University and OCP Policy Center.

Ball L, Furceri D, Leigh D, Loungani P (2019). Does One Law Fit All? Cross-Country Evidence on Okun's Law. Open Economies Review 30(5):841-874.

Baxter M, King R (1999). Measuring business cycle: Approximate bandpass filters. Review of Economics and Statistics 81(4):575-593.

Bell R, McCaffrey D (2002). Bias Reduction in Standard Errors for Linear Regression with Multi-Stage Samples. Survey Methodology 28(2):169-181.

Butkus M, Seputiene J (2019). The Output Gap and Youth Unemployment: An Analysis Based on Okun's Law. Economies 7(108).

Chamberlin G (2011). Okun's Law revisited. Economic and Labour Market Review, pp.104-132.

Chow GC, Lin A (1971). Best Linear Unbiased Interpolation, Distribution, and Extrapolation of Time Series by related Series. The Review of Economics and Statistics 53(4):372-375.

Christiano L, Fitzgerald T (1999). The Band Pass Filter. NBER Working Paper (W7257).

Crespo-Cuaresma J (2003). Revisiting Okun's Law: A Piecewise-linear Approach. Oxford Bulletin of Economics and Statistics 65:439-451.

Denton FT (1971). Adjustment of monthly or Quarterly Series to Annual Totals: An Approach based on Quadratic Minimization. Journal of the American Statistical Association 66(333):99-102.

Enders W (2015). Applied Econometric Time Series (ed. Fourth). Wiley.

Fortin M, Joanis M, Kabore P, Savard L (2022). Determination of Quebec's Quarterly Real GDP and Analysis of the Business Cycle, 1948-1980. Journal of Business Cycle Research 18(3):261-288.

Froot KA, Rogoff K (1995). Perspectives on PPP and long-run real exchange rates. Handbook of International Economics III:1647-1688.

Furceri D (2012). Unemployment and labor market developments in Algeria. Prepared by Davide Furceri. International Monetary Fund.

Gaëtan S (2014). The deformation of Okun's law over the business cycle (p. 01238893). University of Rennes.

Ginsburgh VA (1973). A Further Note on the Derivation of Quarterly Figures Consistent with Annual Data. Applied Statistics 22(3):368-374.

Hansen BE (2000). Sample Splitting and Threshold Estimation. Econometrica 68:575-603.

Hansen B (2022). Jackknife Standard Errors for Clustered Regression. Available at: https://www.ssc.wisc.edu/~bhansen/papers/tcauchy.html

Harris R, Silverstone B (2001). Testing for Asymmetry in Okun's Law: A Cross-country Comparison. Economics Bulletin, 5.

Huang RH (2003). Okun's Law Revisited : A Structural Change Approach. Tamkang University.

Huang RH, Chang Y (2005). Investigating Okun's law by the structural break with threshold approach: Evidence from Canada. The Manchester School 73(5):599-611.

Daly J, Jackson D, Mannix J, Davidson P, Hutchinson M (2014). The importance of clinical leadership in the hospital setting. Journal of Healthcare Leadership 6:75–83.

Huang L, Wang L (2017). Accelerated Monte Carlo simulations with restricted Boltzmann machines. Physical Review B 95:035105

Karim A, Aomar I (2016). Policy Lessons from Okun's Law for Developing Countries. In Global Labor Markets Workshop, pp. 1-46.

Knotek E (2007). How useful is Okun's law. Economic Review 92(4):73-103.

Lamzihri O, El-Kamli M (2021). Estimation of Okun's law with the ARDL model. International Journal of Accounting, Finance, Auditing, Management and Economics 2:680-693.

Lee J (2000). The Robustness of Okun's law: Evidence from OECD countries. Journal of Macroeconomics 22(2):331-356.

Lothian JR, Taylor MP (1996). Real exchange rate behavior: the recent float from the perspective of the past two centuries. Journal of Political Economy 104(3):488-509.

Majaski C (2021). Output Gap: Whatr It Means, Pros & Cons of Using It. In Investopedia. https://www.investopedia.com/terms/o/outputgap.asp/

Marinkov M, Geldenhuys J (2007). Cyclical Unemployment and Cyclical Output: An estimation of Okun's Coefficient for South Africa. South African Journal of Economics 75(3):373-390.

Micallef B (2017). Empirical Estimates of Okun's Law in Malta. Applied Economics and Finance 4(1):138-148.

Michail NA (2015). Examining the stability of Okun's coefficient. Bulletin of Economic Research 71(3):240-256.

Moosa I (1997). A Cross-Country Comparison of Okun's Coefficient. Journal of Comparative Economics 24(3):335-356.

Moosa I (1999). Cyclical output, cyclical unemployment, and Okun's coefficient: A structural time series approach. International Review of Economics and Finance 8(3):293-304.

Okun A (1962). Potential GNP: its measurement and significance. Proceedings of the Business and Economics Statistics Section, pp. 98-104.

Owyang M, Sekhposyan T (2012). Okun's law over the business cycle: Was the great recession all that different? Federal Reserve Bank St. Louis Review 5(94):399-418.

Petkov B (2008). The Labour Market and Output in the UK - Does Okun's Law Still Stand? Bulgarian National Bank, 978-954-8579-17-19.

Pizzo A (2019). Literature review of empirical studies on Okun's Law in Latin America and the Caribbean. Geneva: ILO. Retrieved from https://www.ilo.org/employment/Whatwedo/Publications/working-papers/WCMS_734508/lang--en/index.htm

Prachowny MF (1993). Okun's Law: Theoretical Foundations and Revised Estimates. Review of Economics and Statistics 75:331-336.

Silvapulle P, Moosa AI, Silvapulle MJ (2004). Asymmetry in Okun's Law. The Canadian Journal of Economics 37(2):353-374.

Singh M, Nurudeen I (2022). Does Okun's Law Hold for China? Some Empirical Evidence. Brics Journal of Economics 3(3):173-182.

Stephan G (2014). Okun's law – A meta-analysis. Available at: https://strathprints.strath.ac.uk/48054/5/Perman_etal_MS2014_Okun_meta_analysis.pdf

Vitek F (2010). Output and Unemployment Dynamics during the Great Recession: A Panel Unobserved Components Analysis. International Monetary Fund. Available at: https://books.google.com/books?hl=fr&lr=&id=1JQYEAAAQBAJ&oi=fnd&pg=PA3&dq=Output+and+Unemployment+Dynamics+during+the+Great+Recession:+A+Panel+Unobserved+Components+Analysis,%E2%80%9D&ots=ZalR_WFv0A&sig=Jo0niK96uILhpK7mFh7rdmcBv14

Weber C (1995). Cyclical Output, Cyclical Unemployment, and Okun's Coefficient: A New Approach. Journal of Applied Econometrics 10:433-445.

World Bank (2020). World Development Indicators | DataBank. Available at: https://databank.worldbank.org/source/world-development-indicators

Yahia KA (2018). Estimating Okun's Law for Malta. MPRA Paper. https://mpra.ub.uni-muenchen.de/83961/

Zeileis A, Köll S, Graham N (2020). Various Versatile Variances: An Object-Oriented Implementation of Clustered Covariances. R. Journal of Statistical Software 95(1):1-36.