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Fitting Okun's law for the Swazi Kingdom: Will a nonlinear specification do?

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Abstract

Despite Okun's law being hailed one of the most fundamental pieces within macroeconomic policy paradigm, empirical evidence existing for the Kingdom of Swaziland remains virtually non-existent. Our study fills this void/hiatus in the literature by examining Okun's law for the Swazi Kingdom by using the nonlinear autoregressive distributive lag (N-ARDL) model applied to data collected over 1991 to 2017. To ensure robustness of our empirical analysis, we further apply the Corbae-Oularis (C-O) filter to extract the gap variables required for empirical estimates. Remarkably, we find strong evidence for nonlinear Okun's trade-off between unemployment and output growth in Swaziland with this trade-off being stronger during recessionary periods compared to expansionary periods. Much-needed policy enlightenment is drawn for Swazi authorities from our findings.

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1 INTRODUCTION

Recently, international bodies such as the International Monetary Fund (IMF) and the World Bank have taken a keen interest on the Kingdom of Swaziland which was recently struck with a severe fiscal crisis which bore a multitude of adverse economic repercussions on the economy. Indeed, the source of the budget crisis can be alluded to the infamous global financial crisis of 2007-2008 which sparked the global recession period of 2009 as well as the sovereign European debt crisis of 2010. In the face of a deteriorating global economy, trade activities within the Southern African Customs Union (SACU) region had drastically plummeted and the smaller SACU members like Swaziland and Lesotho were the most affected on account of their fiscal dependence on SACU revenues. The severity of these events is reflected in Swaziland's economic performance over the last decade, with economic growth deteriorating from 6% to 2% between 2006 and 2017 and unemployment rising from 22% to 26% within the same period. By simple arithmetic computation, this would imply that a 4 percentage point reduction in GDP growth has been accompanied by a 4 percentage point increase in unemployment which can be further interpreted as a 1 for 1 trade-off between the two variables.

In our paper we examine whether the observed '1-for-1' negative relationship between economic growth and unemployment in Swaziland is incidental or coincidental. To this end we examine whether Okun's law holds for the Swazi Kingdom and in doing so, our study makes three noteworthy contributions to the empirical literature. Firstly, and as far as we are concerned, this becomes the only empirical study to investigate the validity of Okun's law for Swazi time series data. Secondly, and to the best of our knowledge, our study is the first in the general empirical literature to use the nonlinear autoregressive distributive lag (N-ARDL) model recently introduced by Shin et al. (2014) to estimate the long-run and short-run cointegration relations between unemployment and economic growth. As will be observed in the literature review presented in the following section, the literature has been more recently inclined towards the possibility of a nonlinear Okun's relationship on the basis of reasonably sound theoretical arguments. The perceived nonlinear dynamics within Okuns law provide our justification for relying on a nonlinear cointegration framework. Lastly, and as best as we know, this study will be the first to use the Corbae and Oularis (2006) filter to extract the 'gap' variables required for estimation purposes. This filter is favoured on the premise/grounds of producing superior extracting properties of cycles and trends within time series variables in comparison to other traditional filters.

Against this backdrop, we structure the rest of our paper as follows. The following section presents a brief review of the associated literature. Section 3 of the paper outlines the empirical framework whereas the data and the empirical analysis are presented in section 4 of the paper. The study is concluded in section 5.

2 LITERATURE REVIEW

In a Cowles foundation paper presented in 1962, Okun (1962) demonstrated on how unemployment in the United States, between the period of 1947 and 1960, tended to fall by a one percentage point for every 3 percentage point rise in economic growth. This inverse relationship between unemployment and economic growth has been more popularly branded as the Okun's law and has been perceived as an important link between labour markets and the product market. Sufficient reviews of the flurry of empirical works providing empirical support for a Okun's law is provided in the contributions of Siyal et al. (2013) and Phiri (2015). More recently there has emerged a handful of academics who have contended that linear Okun's specification is inconsistent with basic Keynesian principles in which variations in unemployment and output differ depending on whether the economy is in the upswing or downswing of the business cycle. The resulting speculation of a nonlinear Okun's law is further grounded on three main arguments. Firstly, a nonlinear Okun's specification is highly consistent with the notion of a nonlinear Phillips curve in which the 'sacrifice ratios' differ during different phases of the business cycle. Secondly, the nonlinear Okun's specification is further important for the recently advocated asymmetric monetary policy rules which infer that linear based policy rules produce misleading signals concerning the appropriate policy stance (Schaling, 2004). Lastly, a nonlinear Okun's specification is considered flexible enough to capture output costs that that are cyclically sensitive yet precise enough to use in complex structural macroeconomic models (Filardo, 1998).

From a theoretical perspective, the nonlinear dynamics between unemployment and economic growth can be traced to seminal work of Palley (1993) and further expounded upon in the works of Campbell and Fischer (2000) and Lang and De Peretti (2009). The general theoretical underpinnings insinuate that certain micro-foundations, such as contracts, existing within by heterogeneous firms aggravate asymmetric adjustments in the cycles of job creation and job destruction. More recently, an increasing number of empirical academics have taken advantage of developments in econometric cointegration modelling techniques to validate nonlinear Okun dynamics within the time series data (Lee (2000), Viren (2001) and Harris and Silverstone (2001) for OECD countries, Crespo-Cauresma (2003) and Holmes and Silverstone (2008) for the US, Phiri (2014) for South Africa). We make note that a majority of these nonlinear studies rely on the momentum threshold autoregressive (MTAR) model of Enders and Granger (1998) and Enders and Siklos (2001). Whilst MTAR nonlinearity is established in the cointegration error of the regression, the model retains linearity in the long-run regression parameter estimates. As mentioned in the introduction, our study makes use of the N-ARDL model of Shin et al. (2014) which is nonlinear in both the short-run and long-run parameters. We outline the empirical dynamics of the nonlinear Okun's specification in the following section of the paper.

3 EMPIRICAL FRAMEWORK

In exploring Okun's law for the Kingdom of Swaziland we implement the 'gap version' which can be specified as[1]:

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[1] Initially we estimated both gap versions and first difference versions of Okun's law. However, we received unfavourable results especially in terms of finding significant cointegration effects (i.e. very low F-statistics in our bounds test for cointegration). We believe that this could be caused by the fact that the ARDL framework used in our empirical analysis are dynamic in themselves, incorporating both long-run and short-run dynamics

$(U - U^T) = \alpha + \beta(Y - Y^T) + e_t$ (1)

Where U is the unemployment rate, Y is the GDP growth rate, U^T is the trend component of unemployment, Y^T is trend component of output growth, α is the regression intercept, β is the Okun's coefficient which is presupposed to be negative and significant and e_t is the regression term with properties $e_t \sim N(0, \sigma^2)$. A contentious issue in the literature concerns the measure of potential unemployment and output, (i.e. $(U - U^T)$ and $(Y - Y^T)$, which are unobservable and must be extracted from the actual unemployment and output growth time series. Popular choices from the previous literature for from extracting these unobservable variables are the Hodrick-Prescott (H-P) and Baxter-King (B-K) filters. As mentioned in the introduction section, our study makes use of the Corbae and Oularis (2006) (C-O hereafter) filter which yields superior filtering properties in comparison to other traditional filters found in the literature. In particular, the C-O filter circumvents problems of approximation error associated with 'time domain' filtering techniques by employing a frequency domain approach for extracting specific components of a series which do not require any pre-filtering in the time domain. The authors particular assume that a series, which is an I(1), has a first difference Wold representation with a spectral density $f_w(\vartheta) > 0$. In applying this to our unemployment and output growth series their Fourier transformations are given as:

$$w_{\vartheta}(X) = (1 - e^{\vartheta})^{-1} w_v(\vartheta) - e^{\vartheta}(1 - e^{\vartheta})^{-1} \frac{U_n - U_o}{\sqrt{n}} \quad (2)$$

$$w_{\vartheta}(X) = (1 - e^{\vartheta})^{-1} w_v(\vartheta) - e^{\vartheta}(1 - e^{\vartheta})^{-1} \frac{Y_n - Y_o}{\sqrt{n}} \quad (3)$$

Where $\vartheta = 2\pi s/n$, for s= 0,1,…, n-1 frequency components and an imposed restriction of $(U_n - U_1) = (U_n - U_0)$ and $(Y_n - Y_1) = (Y_n - Y_0)$, respectively.

In estimating regression (1), we firstly specify the Okun's regression as the following autoregressive distributive lag (ARDL) model specification:

$$\Delta(U - U^T)_t = \alpha_0 + \sum_{j=1}^{n} \alpha_1 \Delta(U - U^T)_{t-j} + \sum_{j=1}^{n} \alpha_{12} \Delta(Y - Y^T)_{t-j} + \beta_1(U - U^T)_{t-1} + \beta_2(Y - Y^T)_{t-1} + e_t \quad (4)$$

And by decomposing $(Y - Y^T)$ into its positive and negative partial sum processes results in the following N-ARDL model specifications:

into the regressions. Therefore estimating Okun's law using the first difference version is equivalent to specifying and estimating the variables in their second differences over the short-run seeing that the short-run coefficients in the ARDL framework are already formulated as first differences of the variables. Moreover, our short sample size may be the reason why our results are not robust to the first difference version of Okun's law. We have thus left out the first difference version of Okun's law from our reported empirical design and analysis but the obtained results are available upon request.

$$\Delta(U-U^T)_t = \sum_{j=1}^{p}\psi_i(U-U^T)_{t-j} + \sum_{j=1}^{p}\left(\Phi_j^+(Y-Y^T)_{t-j}^+ + \Phi_j^-(Y-Y^T)_{t-j}^-\right) + \zeta_t \quad (5)$$

Where $(Y-Y^T)_t^+ = \sum_{j=1}^{i}\Delta(Y-Y^T)_j^+ = \sum_{j=1}^{i}\max(\Delta(Y-Y^T)_{,j}, 0)$ and $(Y-Y^T)_t^- = \sum_{j=1}^{i}\Delta(Y-Y^T)_j^- = \sum_{j=1}^{i}\min(\Delta(Y-Y^T)_j, 0)$. In continuing with our modelling process, the associated error correction representation can be denoted as:

$$\Delta(U-U^T)_t = \sum_{j=1}^{p}\rho_i(U-U^T)_{t-j} + \Phi_j^+(Y-Y^T)_{t-j}^+ + \Phi_j^-(Y-Y^T)_{t-j}^- + \sum_{j=1}^{p-1}\lambda_i\Delta(U-U^T)_{t-j} + \sum_{j=0}^{q-1}(\alpha_j^+\Delta(Y-Y^T)_{t-j}^+ + \alpha_j^-\Delta(Y-Y^T)_{t-j}^-) + \lambda ECT_{t-1} + \zeta_t \quad (6)$$

Where ECT_{t-1} is the error correction term. The traverse between short-run disequilibrium and the new long-run steady state of the system can be estimated through the following cumulative dynamic multipliers:

$$M_h^+ = \sum_{j=0}^{n}\frac{\partial y_{t+j}}{\partial x_i^+},\ M_h^- = \sum_{j=0}^{n}\frac{\partial y_{t+j}}{\partial x_i^-}, \qquad h = 0, 1, 2 \ldots. \quad (7)$$

Where M_h^+ and $M_h^+ \rightarrow \beta^+$ and β^-, respectively as $h \rightarrow \infty$, such that the long-run regression coefficients are computed as $\beta^+ = -(\Phi^+/\rho)$ and $\beta^- = -(\Phi^-/\rho)$. To validate N-ARDL cointegration effects Shin et al. (2014) propose the testing of three empirical hypotheses. The first hypothesis tests for asymmetric N-ARDL effects using the following null hypothesis, H_{00}: $\rho = \Phi^+ = \Phi^-$. The second hypothesis tested is that for no long-run asymmetric effects i.e. H_{01}: $\beta^- = \beta^+$. The third null hypothesis tested concerns no short-run asymmetries i.e. H_{02}: $\sum_{i=0}^{q-1}\alpha_j^+ = \sum_{i=0}^{q-1}\alpha_j^-$. Note that the first hypothesis is an extension of the non-standard bounds based F-test of Pesaran et al. (2001) whilst the the latter two null hypotheses of 'no long-run' and 'no short-run' asymmetric effects can be evaluated by relying on standard Wald tests.

4 DATA AND EMPIRICAL RESULTS

4.1 Data overview

Our empirical data is sourced from the World Bank online statistical database and consists of two empirical time series variables, namely, GDP growth (i.e. Y_t) and the unemployment as a percentage of total labour force (i.e. U_t). Our times series covers a period of 1991 to 2017 and our data is collected on an annual basis. From these time series we use the C-O filter to extract the gap variables ($U - U^T$) and ($Y - Y^T$) which we use for empirical analysis. The basic descriptive statistics and the correlation matrix for the gap variables are presented in Appendix A.

4.2 Unit root tests

One of the primary advantages of the ARDL/N-ARDL models is that unlike other cointegration frameworks like the Engle-Granger two-step procedure and the vector error correction (VECM) techniques, the time series are not required to be integrated of similar order for cointegration to occur. On condition that none the series are integrated of order I(2) or higher, the ARDL/N-ARDL models is compatible with a combination of I(0) and I(1) series. To ensure continuity in our argument of nonlinearity in cointegration effects, we compliment this framework by employing the ESTAR unit root testing procedure of Kapetanois et al. (2003) (hereafter KSS) to make certain that none of our time series is integrated of order I(2) or higher. KSS particularly propose the following exponential smooth transition autoregressive (ESTAR) the data generating process for a series, X_t:

$$\Delta X_t = \phi_i X_{t-1} + \gamma_i X_{t-1}[1 - \exp(-\theta X_{t-d}^2)] + e_t \tag{8}$$

Where $e_t \sim iid(0, \sigma^2)$ and θ is a smoothness parameter. KSS further assume (2003) that $\phi_i = 0$ and d=1 i.e.

$$\Delta X_t = \gamma_i X_{t-1}[1 - \exp(-\theta X_{t-1}^2)] + e_t \tag{9}$$

Since testing for a unit root is not directly feasible due to nuisance parameters under the unit root null hypothesis (i.e. $\theta_i = 0$), we apply a first-order approximation around $\theta_i = 0$ and obtain the following auxiliary regression:

$$\Delta X_t = \delta_i X_{t-i}^3 + \sum_{j=1}^{p} \rho_i \Delta X_{t-i} + e_t \tag{10}$$

Where the null hypothesis of a linear unit root process can be now tested as H_0: $\delta_i = 0$ against the alternative of stationary ESTAR process (i.e. H_1: $\delta_i = 0$) and the asymptotic critical value of the Kapetanios et al. (2003) unit root test is computed as:

$$t_{NL} = \frac{\hat{\delta}}{S.E.(\hat{\delta})} \tag{11}$$

Where $\hat{\delta}$ is the estimated value of δ and S.E.($\hat{\delta}$) is the standard error of $\hat{\delta}$. Since the t_{NL} statistic does not follow an asymptotic standard normal distribution, KSS derive critical values for the test statistics performed on raw time series, de-meaned data (i.e. $x_t = y_t - \bar{y}_t$) and de-trended data (i.e. $z_t = y_t - \hat{\mu} - \hat{\delta}t$) where $\bar{y}_t$ is the sample mean and $\hat{\mu}$ and $\hat{\delta}t$ are the OLS estimates of μ and δ, respectively. The results for the KSS unit root test are reported in Table 1 and all reported KSS test statistics exceed their 1% critical values except for the de-trended series of both $(U - U^T)$ and $(Y - Y^T)$ variables when the test is performed on their levels. Nevertheless, when the test is performed in its first difference then all series are stationary at all critical levels. Collectively, this implies that are series are possibly I(0) or I(1) variables but rules out the possibility of the series being I(2) which is a favourable result for our analytical use.

Table 1: KSS unit root test results

Series	Raw	De-meaned	De-trended
Panel A: Levels			
$(U - U^T)$	-6.145942***	-6.145942***	-2.010862
	[1]	[1]	[1]
$(Y - Y^T)$	-4.340919***	-4.340919***	-2.863638
	[1]	[1]	[1]
Panel B: First differences			
$(U - U^T)$	-6.480010***	-6.480010***	-4.152667***
	[1]	[1]	[1]
$(Y - Y^T)$	-8.196387***	-8.196387***	6.299008***
	[1]	[1]	[1]

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively. Critical values are derived from KSS for the raw series -2.82(1%), -2.22 (5%), -1.92(10%), for the de-meaned series -3.48(1%), -2.93(5%), -2.66(10%), for the de-trended series -3.93(1%), -3.40(5%), -3.13(10%). Optimal lags length as determined by the Schwarz criterion reported in [].

4.3 Empirical analysis

Before presenting our main N-ARDL estimates, we first estimate a conventional ARDL (p,q) models with the results reported in Table 2. To determine the optimal lag length of the regression we set the maximum lags of p=4 and q=4 on the ARDL regression and by decreasing the number of lags sequentially on both p and q, we choose the regression which produces the lowest Schwarz criterion (SC) value, which in our case amounts to an ARDL(1,0) specification. Panel A of Table 3 presents the long-run ARDL(1,1) coefficient estimates and as can be witnessed the $(Y - Y^T)$ coefficient produces a correct negative estimate of -0.80 yet is statically insignificant. Nevertheless, the short-run estimates presented in Panel B of Table 3 produces an encouraging coefficient of -0.51 which is statistical significant at all critical levels hence providing evidence of potential short-run Okun effects. Moreover, the error correction term produces the correct negative and statistically significant estimate, which implies convergence of the time series to their steady-state equilibrium in the face of disequilibrium to the system.

Table 2: ARDL(1,0) regression estimates

variable	coefficient	Std. error	t-statistic	Prob
Panel A: Long-run estimates				
C	-0.105210	0.921332	-0.114193	0.9101
$(Y - Y^T)$	-0.796124	0.958050	-0.830984	0.4145
Panel B: Short-run estimates				
$\Delta (Y - Y^T)$	-0.514237	0.173206	-2.968927	0.0069***
ECT_{t-1}	-0.074276	0.008491	-8.746992	0.0004***

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively.

In turning to our N-ARDL estimates, we similarly find that the optimal lag length as selected by the minimization of the SC information criterion points to a N-ARDL (1,1,0) model. However, the N-ARDL(1,1,0) estimates which are presented in Table 3, these results clearly paint a different picture compared to those obtained from the linear ARDL estimates. Judging on the long-run estimates reported in Panel A, one can notice how the long-run estimates still produce insignificant values despite accounting for asymmetries in the cointegration framework. On the other hand, the results obtained of the short-run Okun's estimates are more encouraging with the $\Delta(Y - Y^T)_t^+$ and $\Delta(Y - Y^T)_t^-$ coefficients producing correct negative and statistically significant estimates. The $\Delta(Y - Y^T)_t^+$ estimate of -0.54 implies a percentage increase in the output gap over the short-run decreases the unemployment gap by 0.54 percent. Conversely, the $\Delta(Y - Y^T)_t^+$ estimate of -0.68 implies that a percentage decrease in the output gap increases the unemployment gap by 0.68 percent. Collectively, these results imply different Okun's trade-off during various phase of the business cycle, with the trade-off being more prominent during recessionary phases and less so during expansionary phase

Table 3: N-ARDL(1,1,0) regression estimates

variable	coefficient	Std. error	t-statistic	Prob
Panel A: Long-run estimates				
C	0.726542	2.815228	0.258076	0.7987
$(Y - Y^T)_t^+$	-0.709065	1.007366	-0.703880	0.4889
$(Y - Y^T)_t^-$	-0.843845	1.011312	-0.834406	0.4130
Panel B: Short-run estimates				
$\Delta(Y - Y^T)_t^+$	-0.542891	0.254628	-2.132099	0.0444*
$\Delta(Y - Y^T)_t^-$		0.255166	-2.142791	0.0434*
ECT_{t-1}	-0.676823	0.0086511	-6.643568	0.0005***

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively.

4.4 Sensitivity analysis

In this section of the paper, we perform a sensitivity analysis by employing the non-parametric band pass filter of Christiano and Fitzgerald (2003) (C-F hereafter) to derive our 'gap variables' for empirical purposes. The findings from the linear ARDL model are presented in Table 5 whereas those for the N-ARDL model specification are reported in Table 6. As is the case for the C-O filter, the findings from the C-F filter produce similar results in the sense of establishing negative and statistically significant short-run Okun's coefficients in both linear and nonlinear ARDL specifications whilst we are unable to find any significant long-run estimates. We treat these results are reinforcement over our initial estimates based on gap variables derived from the C-F filter.

Table 4: ARDL(1,0) regression estimates using the C-F filter

variable	coefficient	Std. error	t-statistic	Prob
Panel A: Long-run estimates				
C	0.031013	0.120452	0.257469	0.7999
Y	-0.199022	0.141678	-1.404749	0.1781
Panel B: Short-run estimates				
ΔY	-0.247167	0.099071	-2.494843	0.0232**
ECT_{t-1}	-1.2617774	0.245161	-5.1467708	0.0001***

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively.

Table 5: N-ARDL(1,1,0) regression estimates using the C-F filter

variable	coefficient	Std. error	t-statistic	Prob
Panel A: Long-run estimates				
C	0.167743	0.163929	1.023267	0.3214
$(Y - Y^T)_t^+$	-0.195861	0.141180	-1.387316	0.1844
$(Y - Y^T)_t^-$	-0.206597	0.146035	-1.414710	0.1763
Panel B: Short-run estimates				
$\Delta(Y - Y^T)_t^+$	-0.275540	0.146521	-1.880547	0.0784*
$\Delta(Y - Y^T)_t^-$	-0.224725	0.113493	-1.980078	0.0643*
ECT_{t-1}	-1.283929	0.264632	-4.851754	0.0002***

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively.

4.5 Model evaluation

In order to evaluate the reliability of our estimated ARDL and N-ARDL regressions for the C-O and C-F gap-based Okun specifications, we present three pairs of diagnostic tests and stability analysis which are summarized in Table 7. Firstly, as found in Panel A, we report the linear and nonlinear bounds testing procedures for linear and nonlinear ARDL effects and our produced F-statistics exceed their respective 5 percent critical values. Secondly, we report our test result for the residual diagnostics in Panel B of Table 7 and these test for normality, serial correlation, heteroscedasticity and functional form all indicate that both estimated regressions conform to the classical 'well-behaved' regression assumptions. We finally summarize the findings from the CUSM and CUSUM squares plots in Panel C of Tables 7 of which we find that both ARDL and N-ARDL estimated regressions are stable within their 7 percent critical bounds.

Table 7: Model evaluation diagnostics

	ARDL		N-ARDL	
	C-O	C-F	C-O	C-F
Panel A: Cointegration tests				
Bounds test	6.00050***	6.918506***	7.50940***	4.583953***
Long-run asymmetries			4.83***	3.94**
Short-run asymmetries			5.94***	4.25**
Panel B: Diagnostic tests				
J-B	2.142760	1.80	1.701227	0.59
	(0.342535)	(0.41)	(0.427153)	(0.74)
SC	0.254237	1.144587	1.372943	1.358879
	(0.7777)	(0.3446)	(0.2772)	(0.2888)
Heter.	0.754681	2.021776	1.970677	2.063262
	(0.5926)	(0.1630)	(0.1478)	(0.1455)
RESET	0.764587	1.556151	0.646306	1.535063
	(0.4526)	(0.1392)	(0.5251)	(0.1456)
Panel C: Stability analysis				
CUSUM	Stable	Stable	Stable	Stable
CUSUMSQ	Stable	Stable	Stable	Stable

Notes: "***", "**", "*" denote 1%, 5% and 10% significance levels, respectively. p-values reported in parentheses ().

5 CONCLUSION

Against a backdrop if a deteriorating World economy caused by the global financial crisis and the global recession period, our study sought to investigate whether simultaneous increase in unemployment and decrease in economic growth observed for the Swazi economy are coincidental or incidental. To achieve this feat we investigate whether Okun's law holds for Swazi data over a period of 1991 to 2017 using the recently introduced N-ARDL cointegration model of Shin et al. (2014). We also make use of the Corbae-Oularis filter to extract the gap variables required for estimation purposes. The prime novelty of our study is thus threefold in being the first to estimate Okun's relationship for Swaziland and in also being the first to estimate Okun's law using the more favourable N-ARDL technique as well as being the first to use the powerful C-O filter to extract the gap variables.

Our empirical results are encouraging in the sense that Okun's law is validated over the short-run for both the linear ARDL and N-ARDL model as well being robust to other filtering techniques i.e. C-F filter. The results from the nonlinear specification particularly indicate that Okun's trade-off is more prominent during recessionary periods whilst during expansionary periods the trade-off is not as strong. In turn, this implies that the Swazi economy is very vulnerable towards a combination of high unemployment and low growth during recessionary cycles whilst during expansionary cycle improved growth is not so inclusive as to offset high unemployment rates. Henceforth Swazi policymakers should be concerned with implementing structural reforms aimed at strengthening the link between product and labour markets which would assist in boosting employment during upswings of the business cycle and preventing increased unemployment during downswings of the cycle. Notwithstanding our empirical findings, we note that a serious limitation of our study concerns the small sample size associated with our empirical analysis. Henceforth, we advise future empirical works on the Swazi Kingdom to be conscious of these limitation and attempt to obtain longer datasets to produce more reliable statistical inferences associated with the empirical analysis.

REFERENCES

Campbell J. and J. Fischer (2000) "Aggregate employment fluctuations with micro-economic asymmetries" *American Economic Review* **90**(5), 1325-1345.

Christiano L and T. Fitzgerald (2003) "The band-pass filter", *International Economic Review* **44**(2),435-465.

Corbae P. and S. Ouliaris (2006) "Extracting cycles from nonstationary data" *Econometric Theory and Practice: Frontiers of Analysis and Applied Research, Essays in Honor of Peter C.B. Phillips*, ed. By P. Corbae, B. Hansen, and S. Durlauf, 167-177.

Crespo-Cauresma J. (2003) "Revisiting Okun"s law: a piecewise-linear approach" *Oxford Bulletin of Economics and Statistics*, **65**, 439-451.

Enders W. and C. Granger (1998) "Unit-root tests and asymmetric adjustment with an example using term structure of interest rates" *Journal of Business and Economic Statistics* **16**(3), 304-311.

Enders W. and P. Siklos (2001) "Cointegration and threshold adjustment" *Journal of Business and Economic Statistics* **19**(2), 166-176.

Filardo A. (1998) "New evidence on the output cost of fighting inflation" *Federal Reserve Bank of Kansas City Economic Review* **3rd Quarter**, 33-61.

Harris R. and B. Silverstone (2001) "Testing for asymmetry in Okun"s law: A cross-country comparison" *Economics Bulletin* **5**(2), 1-13.

Holmes M. and B. Silverstone (2008) "Okun's law, asymmetries and jobless recoveries in the United States: A Markov-switching approach" *Economic Letters* **92**(2), 293-299.

Lang D. and C. De Peretti (2009) "A strong hysteresis model for Okun's law: Theory and preliminary investigation" *International Review of Applied Economics* **23**(4), 445-462.

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

Okun A. (1962) "Potential GNP: Its measurement and its significance" *American Statistical Association, Proceedings of the Business and Economics Section*, pp. 98-103.

Palley T. (1993) "Okun's law and the asymmetric and changing behaviour of the USA economy" *International Review of Applied Economics* **7**(2), 144-162.

Phiri A. (2015) "Nonlinear cointegration between unemployment and economic growth in South Africa" *Managing Global Transitions* **12**(4), 303-324.

Schaling E. (2004) "The nonlinear Phillips curve and inflation forecast targeting: Symmetric versus asymmetric monetary policy rules" *Journal of Money, Credit and Banking* **36**(3), 361-386.

Shin Y., Yu B. and M. Greenwood-Nimmo (2014) "*Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework*" Festsschrift in honor of Peter Schmidt: Econometric Methods and Applications, eds. By R. Sickels and W. Horace, Springer, 281-314.

Siyal G., Ahmed A., Aziz A. and K. Zaman (2013) "The long run effects between unemployment and economic growth in selected SAARC countries" *The Economic Research Guardian* **3**(2), 70-85.

Appendix A: Basic descriptive statistics and correlation matrix

Panel A: Descriptive statistics	$(U - U^T)$	$(Y - Y^T)$
Mean	-6.84E-16	-3.78E-16
Median	-0.068863	0.130603
Maximum	2.723538	1.925418
Minimum	-2.274175	-1.897172
Std. dev.	1.335438	1.088551
Skewness	0.311314	-0.035837
Kurtosis	2.652195	2.093512
Jarque-Bera	0.572213	0.930215
Probability	0.751183	0.628068
observations	27	27
Panel B: Correlation matrix		
$(U - U^T)$	1.00	-0.288363
$(Y - Y^T)$	-0.288363	1.00

Notes: Authors own computation on Eviews 10.