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Original Article

Sectoral Growth Patterns and Unemployment in Uganda

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ABSTRACT

Uganda's labour market is typically characterized by extensive productivity and earning variations with large amounts of labour trapped and toiling in low-productivity subsistence activities. A policy aimed at reallocating such underemployed labour to higher productivity activities plays a role in tackling the unemployment problem and is a top priority for policymakers. This study examines the asymmetric effects of differential sectoral growth on unemployment in Uganda, considering both the size and composition effect of sectoral growth. The results of this study indicated that a positive shock in agricultural sector value added has a positive causal effect on unemployment. Also, a positive and negative shock in the industrial sector does not affect the level of unemployment. Finally, both a positive and negative shock in the service sector value added has a negative effect on the unemployment level. Another interesting finding of this study is that both the size and composition of sectoral growth matter in addressing the unemployment problem in Uganda. Therefore, both positive and negative shocks should be forecasted and incorporated in government planning frameworks for short, medium, and long particularly during manpower planning. However, sectors with higher labour intensity should be prioritized in budgetary allocations, the government should devise means of reducing underemployment of labour trapped in low-productivity agriculture and other small-scale production activities to create meaningful employment.

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INTRODUCTION

Unemployment is an important indicator of economic activity in both developed and developing countries, it increases during a recession and recedes as the economy recovers. That said, unemployment is a major concern to governments worldwide, given the negative impacts it has on the economy. This is why UNECA (United Nations Economic Commission for Africa) has identified employment as one of the pillars to spur rapid economic growth among developing countries (Merotto, 2019). According to the 2020 World Bank report on the labour markets in Uganda, approximately 700,000 young people enter the labour market every year to compete for less than 20,000 new jobs created, and this number is projected to reach 1 million between 2030 and 2040 (World Bank, 2020). At this pace, it is projected that 16 million workers will be added to Uganda's workforce in that decade alone. To put this into perspective, in 2020, national and youth unemployment was 3.2 and 5.3 percent respectively, which is an improvement from 9.2 and 11.2 percent reported in 2017 (Uganda Bureau of Statistics [UBOS], 2020). However, by adopting a narrower definition of unemployment, for instance, by excluding volunteers and unpaid family workers and rising hours of work from one to five, these metrics increase to 40 and 39 percent respectively. This implies unemployment metrics in Uganda are significantly understated which sends a wrong signal to the labour markets (Gicharu & Muturi, 2021; NDP II (2015/16 – 2019/20))

Uganda like other developing countries experiences large sectoral productivity and earning differentials. Over 70 percent of the country's employment is generated by informal jobs mainly in low-productive activities in agriculture (Byiers et al., 2015). A large proportion of Uganda's labour force is trapped in the low-productive agriculture sector, signalling under-capacity utilization of labour (Bwire et al., 2016). Yet the reallocation of this labour into more productive sectors has the potential to lower unemployment, improve wages, and ultimately enhance economic growth. The argument that structural transformation from low-productive sectors such as agriculture to manufacturing and ultimately industry improves employment is well-founded in the literature (Feder, 1982; Gemmell, 1982; Lewis, 1954; Syrquin & Chenery, 1989). Given the fact that the reallocation of labour to the more productive sectors not only addresses the scourge of unemployment, it is also a source of economic growth since labour is utilized at its full potential. For example, Byiers et.al (2015) finds that the role of agriculture in Uganda is declining and employment is shifting to the services sector. This, therefore, explains the motivation that policymakers give to the different patterns of sectoral growth.

The impact of sectoral growth differentials as an engine of employment generation and unemployment reduction has been extensively explored in East Asian countries (Noland et al., 2012; Sharma & Singh, 2019). These studies attribute a large reduction in unemployment to the structural transformation from agriculture to export-oriented manufacturing. But, many of the available studies concentrate on the nexus between poverty

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and differences in sectoral growth instead, for instance, Loayza & Raddatz, (2006) examined the impact of agriculture and manufacturing and found that the growth of these sectors rapidly lowered unemployment, and hence poverty. In other words expansion in sectors that accommodate many poor people are more beneficial to economic growth (Arias-Vazquez et al., 2021). In contrast, growth in natural resources as a remedy to unemployment is supported by Caselli & Michaels, (2009); Liu et al., (2020). This literature has come to be known as the "natural resource curse", where countries with abundant natural resources still suffer high unemployment levels. For example, Caselli & Michaels, (2009) find no impact of oil windfall on the standards of living in Brasil. On the contrary, de Janvry & Sadoulet, (2009) argued in favour of agricultural sector transformation, in their argument, a structural transformation from the agricultural sector accelerates industrialization which is vital in unemployment reduction.

Despite a proliferation of empirical studies that have explored unemployment and sectoral growth, very little work has been done on the impact of sectoral-specific growth differentials on unemployment in Uganda in particular. The majority of the available studies address structural transformation and poverty ((Loayza & Raddatz, 2006; Matovu, 2000; Ravallion & Chen, 2004; Ravallion & Datt, 2001; Ssewanyana et al., 2011), and determinants of unemployment (Byiers et al., 2015; Guloba et al., 2022; Mugisha & Kitamirike, 2017; Mukisa et al., 2020). The impact of different sectoral growth patterns on unemployment is much speculated about but barely studied in Uganda, yet this relationship is an important policy question and therefore affects the type of growth strategies adopted by the government. This study fills this gap.

LITERATURE REVIEW

Empirical Literature

Empirically, several influential studies link sectoral growth to labour market performance which motivates our work. This literature follows broadly three strands: (1) the impact of structural transformation on unemployment and poverty (Arias-Vazquez et al., 2021; Basile et al., 2011; Christiaensen & Kaminski, 2015; Lilien, 1982; Loayza & Raddatz, 2006; Ravallion & Chen, 2004; Ravallion & Datt, 1996, 2001; Suryahadi et al., 2008) , (2) sector-specific growth, poverty, and unemployment (Alvarez-Cuadrado & Poschke, 2011; Christiaensen et al., 2010; de Janvry & Sadoulet, 2009; Ellis et al., 2018), and (3) natural resources, poverty and unemployment (i.e., natural resource curse) (Caselli & Michaels, 2009; Mcmillan & Rodrik, 2011). According to Christiaensen & Kaminski, (2015), sector growth can contribute to employment and thus low poverty or unemployment through two channels first through within-sectoral economic growth where assets such as labour and land change (Ravallion & Datt, 1996), and second through inter-sectoral factor mobility from low to high productivity sectors (Mcmillan & Rodrik, 2011), and more recently which Arias-Vazquez et al. (2021) calls structural transformation. Below we discuss this literature further.

One of the earlier studies to examine the impact of sector composition of growth on poverty ws carried out by Ravallion & Datt, (1996) in India using consumption-based poverty measures available for forty years. They found that growth in the primary and tertiary sectors lowered poverty levels, while growth in the secondary sector did not affect poverty in both rural and urban areas. It is argued that the growth or contraction of one sector affects other sectors and thus can result in unemployment and thus poverty. As a follow-up, Ravallion & Datt, (2001) used 20 household surveys from 15 Indian states spanning a period from 1960-1994 to examine

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the impact of the sectoral composition of economic growth on consumption poverty, they found no significant differences in the elasticities of poverty measure across states, but the effect varied appreciably across rural and urban areas for non-farm output which impacted poverty. Extending a similar approach in the case of China after Deng Xiaoping's pro-market reforms of 1978, and applying the newly gathered distributional data spanning 1980–2001, Ravallion & Chen, (2004) found that indeed the pattern of growth is significant in determining unemployment and poverty. Specifically, agriculture contributed more to poverty reduction than both secondary and tertiary sectors, and rural growth as opposed to urban economies which contributed more to unemployment reduction and poverty alleviation.

Relatedly, a study by Loayza & Raddatz, (2006) examined the impact of the sectoral composition of growth on labour market outcomes based on a two-sector theoretical model, using a sample of 55 countries, their results indicate that although overall growth matters for poverty alleviation and thus unemployment, the largest contributions come from agriculture, construction, and specifically manufacturing sector. This argument is in line with (Arias-Vazquez et al., 2021) who find that the greatest benefits are obtained if growth occurs in the sectors that easily employ the poor. Further, the above arguments are in line with the notion of continuous reallocation of labour due to shifts in the demand for employment fronted by Lilien (1982). In a cross-country study using Brazil, Indonesia, and Mexico as case studies, Arias-Vazquez et al., (2021) examined the impact of sectoral growth patterns and employment outcomes. The Authors find that growth in sectors such as mining and utilities increased unemployment, while growth in manufacturing was associated with a reduction in unemployment, rendering support to the "resource curse" phenomenon in employment among middle-income countries. Surprisingly, agriculture, which employs the majority of the people had minimal impact on overall unemployment in low-income countries. Further, the impact of differential sectoral growth on unemployment is significant over a short-run period when labour is immobile.

Turning to sector-specific and unemployment studies, Alvarez-Cuadrado & Poschke, (2011) examined the historical perspective of the drivers of declining agriculture employment. Specifically, the authors focused on two views namely the labour push channel due to improvement in agricultural technology which frees up agricultural labour to other sectors and the labour pull channel where improvements in the technology of other sectors attract labour away from the agricultural sector. Using historical data spanning since the nineteenth century about 12 industrialized countries, the authors found evidence of the dominance of the labour pull channel up until the 1920s, while the labour push channel dominated after the 1960s. They further found that countries in the early stages of structural transformation benefited more from the labour pull channel, which implied more employment in the attractive or growing sectors and more unemployment in the shrinking agricultural sectors. However, the difference in unemployment levels was not directly attributed to sectoral growth differences in this study. In another sector-specific study across several countries, Christiaensen et al. (2010) found that agriculture significantly reduces poverty among the very poor compared to the non-agriculture. But that the non-agricultural sectors have an edge in reducing poverty among the better-off poor. According to this study, a large share of households that participate in the agricultural sector overshadows the contribution of the non-agricultural, especially in developing countries.

In Italy, Basile et al. (2011) assessed the impact of sectoral shifts and industrial specialization patterns on regional unemployment using time series data spanning the period 2004-2008. Results from their semiparametric spatial auto-regressive framework indicated that sectoral shifts and the degree of specialization negatively affects unemployment

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dynamics, exacerbated by the well-known north-south divide that characterizes the Italian labour markets. On the other hand, Ellis et al. (2018) examined the employment potential of Tanzania's services sector between 2002 to 2012. Generally, the authors found that more than 75 percent of labour productivity is attributable to structural change. Specifically, non-agricultural employment improved by 11.4 percent in the formal sector and 88.6 percent in the informal sector. The authors further found that services such as trade significantly contribute to employment, while business services, transport, and communication provide less employment although they are a catalyst for the normal functioning of other firms. Such expositions are unsatisfactory because they do not directly examine the impact of differential sectoral growth on unemployment levels.

In Uganda, Christiaensen & Kaminski, (2015) carried out a study that investigated the impact of long-time sectoral growth patterns on poverty and thus unemployment, they developed a micro-level decomposition approach to study consumption growth and poverty or unemployment reduction, giving more attention to the role of sectoral growth. Based on Panel data spanning the period 2005-2010, the authors find that unemployment dynamics and consumption growth patterns exhibit duality characteristics. Specifically, households that spent more time in agriculture had lower levels of unemployment and poverty compared to those engaged in rural non-farm activities. The study concluded that as the share of labour market participation has increased over time, households have continued to allocate less of their time to agriculture.

Previous studies examining the impact of sectoral growth patterns on unemployment generally report that expansion in sectors that utilize more labour as opposed to capital can reduce unemployment and that natural resource growth may lead to a resource curse instead of lowering unemployment. However, there is no single agreeable position on the role of sectoral growth patterns on unemployment since this evidence varies considerably by context and there is no definitive stand. In other words, although, the link between poverty and growth is well established, that between sectoral growth patterns and unemployment is inconclusive. Therefore, in this study, we provide evidence of how the level of unemployment varies with differential sectoral growth patterns. Further, we investigate whether growth in low or high-productivity sectors affects the level of unemployment differently. In summary, the impact of sectoral growth patterns on labour market outcomes is more speculated about but unfortunately understudied. The question of interest in this study, therefore, is what are there unemployment consequences of sector growth differentials?

METHODOLOGY

Theoretical Model

To investigate the relationship between sectoral growth patterns and unemployment, we adopt and modify the Loayza & Raddatz, (2006) and Arias-Vazquez et al. (2021) two-sector model. Working with a two-sector model is purely for simplicity purposes, however, the model can be extended to n-sectors. For brevity purposes, we only concentrate on important concepts for the derivation and leave out many irrelevant side steps of the processes.

Assuming an economy has two types of agents i.e. those employed and those unemployed similar to the poor-rich analogy of Loayza & Raddatz, (2006). These agents possess l_i units of labour and maximize utility $U(C) = \log(C)$ with same discounting factor γ.

The employed agents receive income I_i which can be passed across generations. In this arrangement, the real wage of the employed agents is dependent on the income and consumption that they earn and make. For simplicity, we assume changes in the unemployment level depend on changes in the real

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wage. For example, when workers demand more wages, employers cut down on the labour force hence causing unemployment, similar to the efficiency wage hypothesis (see; Pissarides, 1998)). In this setup, the production of output y follows a constant elasticity of substitution (CES) production technology given below;

$$y = \left(x_1^{\delta} + x_2^{\delta}\right)^{\frac{1}{\delta}} \quad (1)$$

Where x_1 and x_2 are inputs in the production process, and the intermediate good production depends on Cobb Douglas production function augmented by labour given as below;

$$x_i = k_i^{(1-\alpha_i)} (A_i L_i)^{\alpha_i} \quad (2)$$

Where $A_i = e^{(g_i t)}$ is the level of technology, sector i employs labour l_i and capital k_i, the capital in the model is highly mobile across sectors and depreciates at a zero rate.

To derive the impact of sectoral growth patterns on unemployment, we start with the link of growth to the real wage rate. We assume profit maximization of a perfectly competitive market;

$$p = (p_1^{1-\varepsilon} + p_2^{1-\varepsilon})^{\frac{1}{1-\varepsilon}} \quad (3)$$

Where $\varepsilon = (1-\delta)$, differentiating equation (3) with respect to output Y, we obtain first-order conditions (FOC) as below;

$$P_i \left(\frac{y_i}{Y}\right) = s_i \left(\frac{y_i}{Y}\right)^{\frac{\varepsilon-1}{\varepsilon}} \quad (4)$$

Solving all the first-order conditions gives the demand function (i.e., the Marshallian) of the intermediate goods;

$$\frac{y_1}{y_2} = \left(\frac{p_2}{p_1}\right)^{\varepsilon} \quad (5)$$

Taking into account the demand for labour and capital under perfect competition, equation (5) becomes

$$y_i = \frac{\omega l_i}{p_i \alpha_i} = \frac{r k_i}{p_i(1-\alpha_i)} \quad (6)$$

The allocation of capital and labour across sectors if equilibrium conditions for the factor markets i.e. $(k_1 + k_2 = k)$ and labour $(l_1 + l_2 = l)$ are known, then equations 5 and 6 enable us to examine the changes in real income of labour, i.e., the ultimate goal is to derive the growth path of the real wage below;

$$\frac{d\omega}{\omega} = \frac{dP_1}{P_1} + \frac{dy_1}{y_1} - \frac{dl_1}{l_1} \quad (7)$$

Where $\frac{dl_1}{l_1}$ is the change of employment in sector 1 and $P_1 y_1$ is the value of sector 1 whose change is given as $\frac{dP_1}{P_1} + \frac{dy_1}{y_1}$, using a similar analogy equation (4) can be written as

$$\frac{ds_1}{s_1} + \frac{dY}{Y} = \left(\frac{\varepsilon-1}{\varepsilon}\right) y_1 + \frac{1}{\varepsilon}\left(s_1 \frac{dy_1}{y_1} + s_2 \frac{dy_2}{y_2}\right) \quad (8)$$

Solving equations (5) and (8) with respect to labour L, with the evolution of labour in sector 1 is given as $\frac{dl_1}{l_1}$, then;

$$\left(\frac{\alpha_1}{\alpha_2}\right)\left(\frac{l_2}{l_1}\right)\left(\frac{y_1}{y_2}\right)^{\frac{\varepsilon-1}{\varepsilon}} = 1 \quad (9)$$

Using the labour market clearing condition $(l_1 + l_2 = l)$, the rate of growth of employment in sector 1 is given as

$$\frac{dl_1}{l_1} = \frac{l_2}{L}\left(\frac{\varepsilon-1}{\varepsilon}\right)\left(\frac{dy_1}{y_1} - \frac{dy_2}{y_2}\right) + \frac{dL}{L} \quad (10)$$

Where $\frac{dL}{L}$ is the change in the overall employment in the economy, thus solving equations 8 and 10 gives the evolution of real wage rate as;

$$\frac{d\omega}{\omega} = \sum_{i=1}^{2} s_i \frac{dy_i}{y_i} + \left(\frac{\varepsilon-1}{\varepsilon}\right) \sum_{i=1}^{2} (l_i - s_i)\, y_i \quad (11)$$

$$(l_i - s_i) = \frac{1}{1+\left(\frac{\alpha_{-i}}{\alpha_i}\right)\left(\frac{s_{-i}}{s_i}\right)} - \frac{1}{1+\left(\frac{s_i}{s_{-i}}\right)} \quad (12)$$

Equation (11) and (12) implies that the growth of real labour incomes is driven by per-capita GDP

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growth. For instance, higher per capita GDP attracts higher output per worker which in return leads to higher wages. The sectoral growth contribution is captured by its share of the final good output s_i

The impact of sectoral growth on wage rate is dependent on the level of elasticity of substitution across the production of the final good and sectors' labour share $(l_i - s_i)$. For simplicity, we assume that an increase in real wage relates to unemployment linearly as below

$$\frac{du}{u} = \beta_0 + \beta_1 \frac{d\omega}{\omega} \qquad (13)$$

This implies changes in unemployment can be expressed as a function of sectoral growth

$$\frac{du}{u} = \beta_0 + \beta_1 \left(\sum_{j=1}^{I} s_i \frac{dy_i}{y_i}\right) + \beta_2 \left(\sum_{j=1}^{I}(l_i - s_i)\frac{dy_i}{y_i}\right) \qquad (14)$$

Simplifying the equation further we obtain

$$\frac{du}{u} = \beta_0 + \sum_{i=1}^{I}\left(\beta_1 - \beta_2 + \beta_2 \frac{L_i}{s_i}\right) s_i . \frac{dy_i}{y_i} \qquad (15)$$

Equation (15) indicates that the impact of sectoral growth on unemployment is mediated by the sector's labour intensity $\left(\frac{L_i}{s_i}\right)$, since different sectors have different labour intensities, the unemployment consequences of growth across different sectors are not the same, this is our conjuncture to be tested in this study. In regression form, equation (15) can be written as

$$\frac{du_t}{u_t} = \beta_0 + \beta_1 \frac{dy_j}{y_j} + \beta_2 \left(\sum_{i=1}^{I}\left(\frac{L_i}{s_i} - 1\right)\right) s_i . \frac{dy_i}{y_i} + \mu_i \qquad (16)$$

Where the impact of change in GDP growth on unemployment is captured by β_1 , while the impact of sectoral growth differentials (proxied by sectoral labour intensity) is captured by β_2. Equation (16) is estimated based on none linear Autoregressive Distributed Lag (NARDL) model. The choice of the NARDL model is because we believe that the unemployment consequences of an increase in sectoral growth are different from that of a decrease in sectoral growth. Our final model (16) is derived from the theoretical underpinnings of unemployment and sectoral growth which connects the theory and empirical analysis in this study.

Empirical Strategy

To estimate the asymmetric impacts of sectoral growth and sectoral growth differences (proxied by labour intensity) on unemployment, we adopted a recent and more flexible dynamic Nonlinear Autoregressive Distributed Lag model (NARDL) (Shin et al., 2014), which is an upgraded version of the standard ARDL model by Pesaran et al. (2001). From equation (16), let $\frac{du_t}{u_t} = Unemp$, $\frac{dy_i}{y_i} = GDP$, and $\left(\frac{L_i}{s_i} - 1\right) = Labor\ intensity\ (Lab)$, the ultimate goal is to estimate the impact of sectoral growth patterns on unemployment, thus a standard NARDL model is specified as;

$$Unemp_t = f(GDP_{it}^{+}, GDP_{it}^{-}, Lab_{it}^{+} Lab_{it}^{-}) \qquad (17)$$

To capture the effect of asymmetry, the NARDL model decomposes explanatory variables into two parts, i.e., the partial sum of positive change in per capita GDP indicated as GDP_{it}^{+} and the partial sum of negative change denoted as GDP_{it}^{+}, as well as labour intensity, i denotes sectors.

Following (Shin et al., 2014) and (Cho et al., 2019), an estimable version of equation (17) in its conditional error correction (CEC) form i.e. NARDL (p, q_j) is given as;

$$\Delta Unemp_t = \sum_{j=0}^{p-1} \lambda_i \Delta Unemp_{t-1} + \sum_{j=0}^{q} \delta_1^{+} \Delta GDP_{t-i}^{+} + \sum_{j=0}^{q} \delta_1^{-} \Delta GDP_{t-i}^{-} + \sum_{j=0}^{q} \delta_2^{+} \Delta Lab_{t-i}^{+} + \sum_{j=0}^{q} \delta_2^{+} \Delta Lab_{t-i}^{-} + \rho Unemp_t + \varphi_1^{+} GDP_{t-i}^{+} + \varphi_1^{-} GDP_{t-i}^{-} + \varphi_2^{+} Lab_{t-i}^{+} + \varphi_2^{-} Lab_{t-i}^{-} + \varepsilon_t \qquad (18)$$

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Where the NARDL (p, q_i) short-run coefficients are λ_i, δ_1^+, δ_1^-, δ_2^+ and δ_2^- and long-run coefficients are ρ, φ_1^+, φ_1^- φ_2^+ and φ_2^-, while ε_t is the error term. The partial sums are computed as follows, for an increase $GDP_t^+ = \sum_{j=1}^{t} \Delta GDP_j^+ = \sum_{j=1}^{t} \max(\Delta GDP_j, 0)$, while for a decrease $GDP_t^- = \sum_{j=1}^{t} \Delta GDP_j^- = \sum_{j=1}^{t} \min(\Delta GDP_j, 0)$. From Equation (18), unemployment enters as an autoregressive process of order p, while, sectoral growth and labour intensity enters as asymmetrically distributed lag variables with orders q_j, where j is the number of lags of the independent variables.

The first step is to estimate the NARDL model based on OLS, secondly, we test the NARDL Bounds test of cointegration and finally we test for long and short-run asymmetry using the Wald test. Similar to the traditional ARDL bounds test, the NARDL bounds test is also a joint test of all lagged one-period levels of GDP_t^+, GDP_t^- and $Unemp_t$. We implement the F-test of Pesaran et.al (2001) since we have a reasonable sample, the null hypothesis is $H_0 = \rho = \varphi_1^+ = \varphi_1^-$ and $H_0 = \rho = \varphi_2^+ = \varphi_2^-$, in case we reject the null, we shall conclude that the variables are cointegrated in the presence of asymmetry.

To test long-run asymmetry, we calculate the NARDL long-run asymmetric coefficients by diving the negative of the coefficients of GDP_1^+ (i.e. φ_1^+) by the coefficient of $Unemp_t$ (i.e. ρ) given as $L_{M1+} = -\frac{\varphi_1^+}{\rho}$, similarly for GDP_1^- is given as $L_{M1-} = -\frac{\varphi_1^-}{\rho}$, using the Wald test for long-run asymmetry, if a long-run relationship exists (i.e. Bounds test), we proceed to test if the difference in the asymmetric coefficients is statistically significant as below

$$H_0: -\frac{\varphi_1^+}{\rho} = -\frac{\varphi_1^-}{\rho}, H_A: -\frac{\varphi_1^+}{\rho} \neq -\frac{\varphi_1^-}{\rho} \qquad (19)$$

If we reject the null hypothesis, it means we have evidence for long-run asymmetry. In other words, the magnitude of the change in unemployment when per capita GDP growth and labour intensity increase is not the same when they decrease. For the short-run asymmetric, the null hypothesis is given as $H_0 = \sum_{j=0}^{q} \delta_1^+ = \sum_{j=0}^{q} \delta_1^-$, if the null is rejected then we conclude that the impact of per capita GDP and labour intensity on unemployment is asymmetric. Finally, we compute asymmetric dynamic multipliers which tell us how unemployment adjusts to its new long-run equilibrium following a positive and negative shock to per capita GDP and sectoral labour intensity. The cumulative dynamic multipliers for the effect of GDP_t^+ and GDP_t^- are evaluated as

$$M_n^+ = \sum_{j=0}^{n} \frac{\partial Unemp_{t+j}}{\partial GDP_{it}^+}, M_n^- = \sum_{j=0}^{n} \frac{\partial Unemp_{t+j}}{\partial GDP_{it}^-} \qquad (20)$$

$, for\ n = 0, 1, 2 \ldots.$

Where, if $n \to \infty$, then $M_n^+ \to \frac{\varphi_1^+}{\rho}$ and $M_n^- \to \frac{\varphi_1^+}{\rho}$

The advantage of the NARDL model unlike the traditional ARDL framework is that it allows for the computation of asymmetric dynamic multipliers, which trace asymmetric pathways of adjustment of each nonlinear distributed lag regressor to its long-run (cointegrating) state. Similar to the traditional VAR's impulse response curves. Further, the standard ARDL model ignores asymmetric effects in variable relationships. Shin and his co-authors solved this problem by incorporating asymmetry by decomposing explanatory variables into their positive and negative partial sums of the distributed lag (Shin et al., 2014). In short, the NARDL model accommodates both long-run (i.e., cointegration) and short-run (i.e., dynamic) relationships.

Data Source

The main source of data was the World Bank Development Indicators (WB) database, secondly, data on unemployment was retrieved from the ILOStat database supplemented by data from

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Uganda Bureau of Statistics (UBOS) labour surveys, the series span the period from 1980 to 2020. Unemployment data in particular is limited for periods before 1990 and thus most of the data is imputed from Uganda labour surveys, complemented with other international labour statistics from ILO and World Bank

RESULTS AND DISCUSSION

Before embarking on the full-scale regression analysis, it is imperative to examine the descriptive properties of our data. First, a descriptive summary of statistics is performed followed by several tests to examine the time series properties of our data. The results are discussed below.

The results from *Table 1* show that the average unemployment rate is 2.3%, while the industrial sector has the highest value-added annual growth at 8.6% followed closely by the services sector at 6.8%, and finally agriculture for the period under study. On the other hand, the services sector recorded the highest valued added contribution to GDP at 41.7% followed by agriculture at 31.4% while the industrial sector value has stagnated at less than a quarter, similar statistics have been reported by Byiers et al. (2015). Although agriculture's contribution to GDP has been declining, its contribution to employment has been growing averaging 70.2% compared to 22.2% and 7.5% for the services and industrial sectors respectively. Most of Uganda's agriculture is subsistence which is less skill-intensive, implying people with no skills in agriculture can still find employment in this sector.

Table 1: Descriptive Statistics

Variables	Obs	Mean	Max	Min	Std. Dev.
Unemployment rate (UNEMP)	41	2.353	3.600	0.890	0.856
Agric-VA annual growth (Y_{Agic})	41	3.100	9.332	-0.983	2.428
Industrial-VA annual growth (Y_{indus})	41	8.612	20.256	2.143	3.979
Services-VA annual growth (Y_{Serv})	41	6.780	13.240	-8.813	3.939
Agric-VA % of GDP (S_{Agric})	41	31.394	53.283	21.385	9.983
Industrial-VA % of GDP (S_{Indus})	41	20.972	26.620	10.415	5.438
Services-VA % of GDP (S_{Serv})	41	41.747	52.032	30.480	5.654
Employed in services as % of total employment (L_{Serv})	41	22.186	25.850	18.890	1.993
Employed in Agric as % of total employment (L_{Agric})	41	70.272	72.680	66.140	2.215
Employed in Indus as % of total employment (L_{Indus})	41	7.552	8.020	6.540	0.522

Note: VA: value added

The ultimate goal of this study is to examine the size and asymmetries which Uganda's sectoral growth patterns may exert on the unemployment rate. Before embarking on regression analysis, it is important to investigate the time series properties of data that we are dealing with, starting with the order of integration, lag selection, and unit root based on the Augmented Dickey-Fuller and Phillips-Perron (PP) test, results are discussed below:

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Table 2: Time Series Unit Root Tests

Variables	Level		First Difference		Order
	ADF	PP	ADF	PP	
UNEMP	-2.437	-2.086	-3.816***	-3.830	I (1)
Y_{Agic}	-5.968***	-5.952***	-3.656***	-10.067***	I (0)
Y_{indus}	-2.813	-2.814	-5.417***	-8.173***	I (1)
Y_{Serv}	-5.887***	-5.916***	-5.071***	-23.813***	I (0)
S_{Agric}	-2.250	-2.351	-5.551***	-5.552***	I (1)
S_{Indus}	-1.966	-1.997	-6.558***	-6.602***	I (1)
S_{Serv}	-2.396	-2.155	-1.866	-7.115***	I (1)
L_{Agric}	-1.344	-1.458	-4.818***	-4.817***	I (1)
L_{Indus}	-0.095	-0.154	-4.919	-4.903***	I (1)
L_{Serv}	-1.859	-1.905	-4.737***	-4.737***	I (1)

Note: ADF: Augmented Dickey-Fuller, PP: Phillips-Perron test

It can be observed from *Table 2* above that its only agriculture value-added annual growth (i.e., Y_{Agic}) and services value-added annual growth (i.e., Y_{Serv}) which are stationary at level (i.e., I (0)) since their p-values associated with their respective test statistics are less than 0.05. The rest of the study variables are non-stationary at the level I(1) thus necessitating differencing of the variables (Woolridge, 2000). After first differencing I(1), unemployment rate (UNEMP), industrial value added annual growth (Y_{indus}), agriculture value added as % of GDP (S_{Agric}), industrial value added as % of GDP (S_{Indus}), services value added as % of GDP (S_{Serv}), employment in services as % of total employment (L_{Serv}), employment in agriculture as % of total employment (L_{Agric}) and employment in industrial sector as % of total employment (L_{Indus}) all become stationary at first difference i.e., I(1). In this case, both tests are in agreement. Given that we have a mixture of both I(0) and I(1) but not I(2) variables, Pesaran et al. (2001) and Pesaran & Shin, (1998) recommended the estimation of an Autoregressive Distributed Lag (ARDL) model. However, since our goal is to investigate asymmetries between sectoral growth and sectoral labour intensities on the unemployment level, we instead adopt a nonlinear ARDL framework by Shin et al. (2014).

According to Cho et al. (2021) the Nonlinear ARDL model provides consistent parameters even if the variables possess different levels of integration. The NARDL model has the superior advantage of being highly flexible in the way that it even accommodates partial asymmetry (ARDL (2, 0, 2, 1, 2, 0, 0)). In this study, the ultimate goal is to examine how the sectoral composition of growth affects unemployment levels. The conjuncture made in this study is that growth in some sectors is more unemployment-reducing than in other sectors and this might have depended on the level of labour intensiveness of this sector.

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Table 3: NARDL Long Run Form and Bounds Test/Conditional ECM

Variable	Coefficient	Std. Error	t-Statistic	Prob.
UNEMP (-1)	-0.2431	0.1884	-1.2903	0.2179
AGRIC_POS	0.0101	0.0711	0.1425	0.0287
AGRIC_NEG(-1)	-0.0070	0.0568	-0.1239	0.9032
INDUS_POS(-1)	-0.0311	0.0527	-0.5902	0.5644
INDUS_NEG(-1)	-0.0293	0.0540	-0.5424	0.5961
SERV_POS	-0.0507	0.0258	-2.2350	0.0422
SERV_NEG	-0.0378	0.0235	-1.6072	0.0303
D(UNEMP(-1))	0.5091	0.2282	2.2305	0.0426
D(AGRIC_NEG)	0.0553	0.0563	0.9830	0.3423
D(AGRIC_NEG(-1))	0.1494	0.0517	2.8886	0.0119
D(INDUS_POS)	0.1248	0.0647	1.9286	0.0473
D(INDUS_NEG)	-0.1328	0.0590	-2.2529	0.0408
D(INDUS_NEG(-1))	0.0890	0.0478	1.8621	0.0137
C	0.8057	0.6207	1.2979	0.2153
Selected Model: ARDL(2, 0, 2, 1, 2, 0, 0)				

The NARDL Bounds test for cointegration estimation has four separate important parts to it, first is the asymmetric Conditional Error Correction (CEC) regression, composed of long-run and short-run (i.e., with difference operators) components, the second is the output of the long-run level, the third is the error correction term which is the residual definition of the long-run model which includes the coefficient of the long-run model. Lastly is the F-Bounds test reported in *Table 6*. The results from the model summary in *Table 3* above indicate that the NARDL model fitted passes all the diagnostic model estimation requirements and thus the results are free from autocorrelation. The efficient model selected is ARDL (2, 0, 2, 1, 2, 0, 0). The R-square of 0.8794 and its F-stat of 7.8526 indicate that the explanatory variables included in the model are sufficient to explain sectoral growth patterns and their impact on the unemployment rate in Uganda. These arguments are derived from (Baltagi, 2021, p. 32) and (Greene, 2002, p. 84)

So, considering the long-run components, we find that a positive shock in the agriculture value-added annual growth (AGRIC_POS) has a positive causal effect on the unemployment rate. On the other hand, a negative shock in the agriculture value-added annual growth in the previous period (AGRIC_NEG(-1)) has a negative association with unemployment, although the effect is not significant. Considering the impact of industrial sector growth on unemployment, we found that both positive and negative shock to the industrial value added in the past period i.e., INDUS_POS(-1) and INDUS_NEG(-1) do not have a causal effect on unemployment, although they are negatively related to the unemployment rate in Uganda. The limited impact of the industrial sector on the unemployment and labour market, in general, is due to the small size of the industrial contribution to both economic growth and the labour market. According to Ggoobi et al. (2017) and Shinyekwa et al. (2016) industrial sector has stagnated and has been overtaken by the services sector due to early government withdrawal from the industrial sector leaving it unprepared private sector. The few industries that are available employ mostly Indians and Chinese leaving Uganda to occupy the poorly remunerated positions. With regard, to the impact of services value-added annual growth on unemployment, it was found that both a positive (SERV_POS) and negative (SERV_NEG) shock in the services sector in the current period has

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a negative causal effect on unemployment level. Specifically, this implies that a 1% positive and negative shock to the services sector is associated with a 0.05 and 0.04% reduction in the unemployment rate.

Concerning the short-run coefficients (i.e., with difference operator), first, it was found that a 1% change in the previous unemployment rates (i.e., D(UNEMP(-1))) has a significant causal effect on the unemployment rate. Specifically, unemployment increases by 0.51% when the previous unemployment rate changes by 1% ceteris peribus. Returning to sectoral growth, results indicated that a negative shock in agricultural value-added annual growth (D(AGRIC_NEG)) has no causal effect on unemployment in the current period. However, the effect becomes significant for the past period, specifically, a 1% negative shock in the agricultural sector value added annual growth significantly increases unemployment by 0.15% in the past period. For the industrial sector, the results indicate that a positive shock in the industrial value added (D(INDUS_POS)) has a positive causal effect on unemployment. Specifically, a 1% positive shock in the industrial value added significantly increases the unemployment rate by 0.12%, this may sound surprising but establishing or increasing industrial capacity is an expensive venture which requires a lot of capital and thus this implies in the short-run, it is difficult for the industrialist to adjust productivity to take advantage of a positive shock thus unemployment will persistent amidst a positive shock. On the other hand, a negative shock in the industrial sector has a significant causal effect on the unemployment rate, particularly unemployment is lowered by 0.13% when the industrial sector experiences a negative shock in the current period.

Finally, it was found that a negative shock in industrial value-added annual growth in the past period had a positive causal effect on unemployment. Specifically, a 1% decrease in the industrial value added (i.e., D(INDUS_NEG(-1))) in the past period expands the unemployment rate by 0.09% other fact holding constant, because our parameters are simply ordinary least squares (OLS) estimates. Below is the levels equation which gives long-run asymmetric coefficients that are computed as the negative ratio of the long-run coefficients from the asymmetric conditional error correction (CEC) model and the lagged term of the dependent variable. The coefficients from the levels equation are used to compute the asymmetric cointegrating equation (i.e., asymmetric long-run equation) as in *Table 4*.

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Table 4: Conditional ECM for the impact of labour intensity on unemployment

Variable	Coefficient	Std. Er	t-Stat	Prob.
UNEMP(-1)	-0.4624	0.0955	-4.8444	0.0004
AGRIC_POS(-1)	-3.3568	0.4368	-7.6818	0.0001
AGRIC_NEG(-1)	2.0439	0.4067	6.9924	0.0000
INDUS_POS(-1)	68.212	10.7262	6.3595	0.0000
INDUS_NEG	0.0781	2.2094	0.0353	0.9724
SER_POS(-1)	30.454	5.5892	5.4488	0.0001
SER_NEG(-1)	10.496	4.9367	2.1262	0.0509
D(UNEMP(-1))	0.1285	0.1027	1.2519	0.2345
D(AGRIC_POS)	3.2076	0.6038	5.3126	0.0002
D(AGRIC_POS(-1))	1.7464	0.3793	4.6044	0.0006
D(AGRIC_NEG)	-0.7592	0.2176	-3.4890	0.0045
D(AGRIC_NEG(-1))	-0.5971	0.1998	-2.9885	0.0113
D(INDUS_POS)	-23.5896	7.8463	-3.0065	0.0109
D(SER_POS)	-7.8695	5.3867	-1.4609	0.0297
D(SER_NEG)	20.568	2.6004	7.9096	0.0000
C	0.8411	0.2433	3.4574	0.0047
Selected Model: ARDL(2, 2, 2, 1, 0, 1, 1)				

The variables from *Table 4* above is computed as a product of the per capita GDP growth (i.e., size effect ($s_i y_i$)) and sectoral labour intensity (i.e., $\frac{L_i}{S_i}$), this ratio captures the effect of the growth composition by decomposing overall GDP growth into their respective sectoral growth contributions. A similar formulation has been adopted in growth poverty nexus studies by Ravallion & Chen, (2004) and Loayza & Raddatz, (2006). Results from *Table 4* above capture the impact of different sectoral growth patterns (i.e., proxied by sectoral labour intensity) on the unemployment level. We observe that in the long run, both positive shock (AGRIC_POS(-1)) and negative shock (AGRIC_NEG(-1)) in the past period have a causal effect on the unemployment rate. Specifically, a 1% positive and negative shock in the agricultural sector labour intensity lowers and increases the unemployment rate by 3.4 and 2.0%. Considering the industrial sector, we find that a positive shock in the industrial sector labour intensity in the past period (INDUS_POS(-1)) significantly lowers the unemployment rate. While a negative shock (INDUS_NEG) in the industrial sector labour intensity in the current period does not affect the unemployment rate. Turning to the services sector, results indicate that both the positive (SER_POS(-1)) and (SER_NEG(-1)) shocks to the services sector labour intensity in the past period have a positive causal effect on unemployment since their coefficients are positive and significant.

In the short-run, we find that a positive shock in agricultural sector labour intensity in both current and past periods (D(AGRIC_POS)) and D(AGRIC_POS(-1)) have a positive causal effect on the unemployment rate. On the other hand, a negative shock in agricultural sector labour intensity in both the current (D(AGRIC_NEG)) and past periods (i.e., D(AGRIC_NEG(-1))) has a significantly negative causal effect on the unemployment rate. For the industrial sector, we find that a positive shock in the industrial sector labour intensity (D(INDUS_POS)) significantly lowers the unemployment rate. Finally, for the services sector, we find that unemployment is a negative function of both positive (D(SER_POS)) and negative (D(SER_NEG)) shocks in the services

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sector labour intensity. Specifically, if services sector labour intensity increases, the unemployment rate reduces by 7.8% otherwise a decrease in services sector labour intensity increases unemployment increases by 20.6%, ceteris peribus.

Table 5: Bounds Test

Sectoral growth model 1				Labour intensity model 2			
Null Hypothesis: No levels relationship				Null Hypothesis: No levels relationship			
F-statistic	**Signif.**	**I (0)**	**I (1)**	**F-statistic**	**Signif.**	**I (0)**	**I (1)**
19.28992	10%	1.990	2.940	3.151983	10%	2.12	3.23
K=6	5%	2.270	3.280	K=6	5%	2.45	3.61
	2.50%	2.550	3.610		2.5%	2.75	3.99
	1%	2.880	3.990		1%	3.15	4.43

From the results above, given that the F-statistic=19.289 exceeds the upper Bounds critical values i.e. I(1) statistics at all levels of significance, we reject the null hypothesis implying that the series are cointegration when all the series are I(1), i.e. this means we have evidence for a long-run relationship among the variables (Shin et al., 2014). The bounds test is performed on the coefficients based on the coefficients of long-run terms under the Error correction model (ECM). According to (Pesaran et al., 2001), we need to proceed to perform the t-bounds test (i.e. t-bounds statistics =-8.56) which is below all the critical values hence reconfirming our earlier hypothesis of no cointegration rejection. Lastly, to confirm if cointegration in the series is either or not degenerate, we perform a Wald test of joint parameter significance using all coefficients for the distributed lag variables at levels and the results are reported in *Table 6*.

Table 6: Wald test of asymmetric between sectoral growth and unemployment

Test Statistic	Agriculture		Industry		Services	
	Value	**P-value**	**Value**	**P-value**	**Value**	**P-value**
t-statistic	-2.324	0.035	-2.955	0.010	-0.842	0.414
F-statistic	5.403	0.035	8.737	0.010	0.708	0.414
Chi-square	5.403	0.020	8.737	0.003	0.708	0.399

Note: The test is computed by equating the fraction of positive to negative coefficients

From the results above, since the p-values for agriculture and industry are less than 0.05, this points to the evidence of long–run asymmetry of the agriculture and industrial value-added annual growth concerning unemployment i.e., there is a long-run asymmetry between unemployment and the growth of agricultural and industrial sector value-added growth. while the services sector shows weak asymmetry. This further reconfirms that cointegration confirmed under the bounds test is non-degenerate. Similar results are replicated for labour intensity, we find evidence of long-run asymmetry between unemployment and agricultural and industrial sector labour intensity.

Diagnostic Tests

Stability Tests

From the cumulative sums (CUSUM) and cumulative sums squares (CUSUMQ), it was observed that in both graphs the blue line lies within the 5% boundary (i.e., 95% confidence interval), this is indicative of model stability. This is important to avoid inconsistent parameters.

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Figure 1: Graph of the cumulative sum (CUSUM) of recursive residuals, the red lines indicate the upper and lower confidence interval bounds.

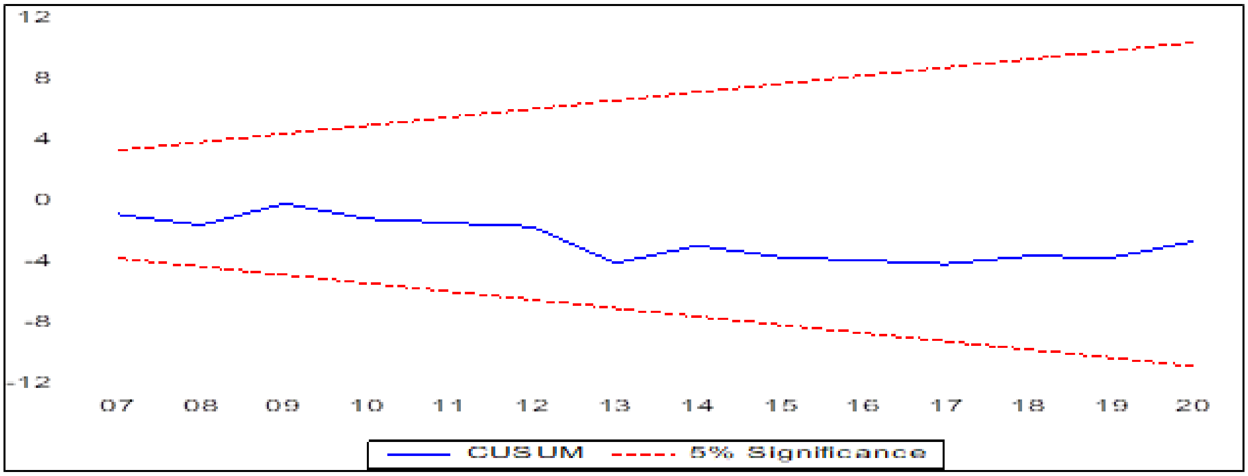
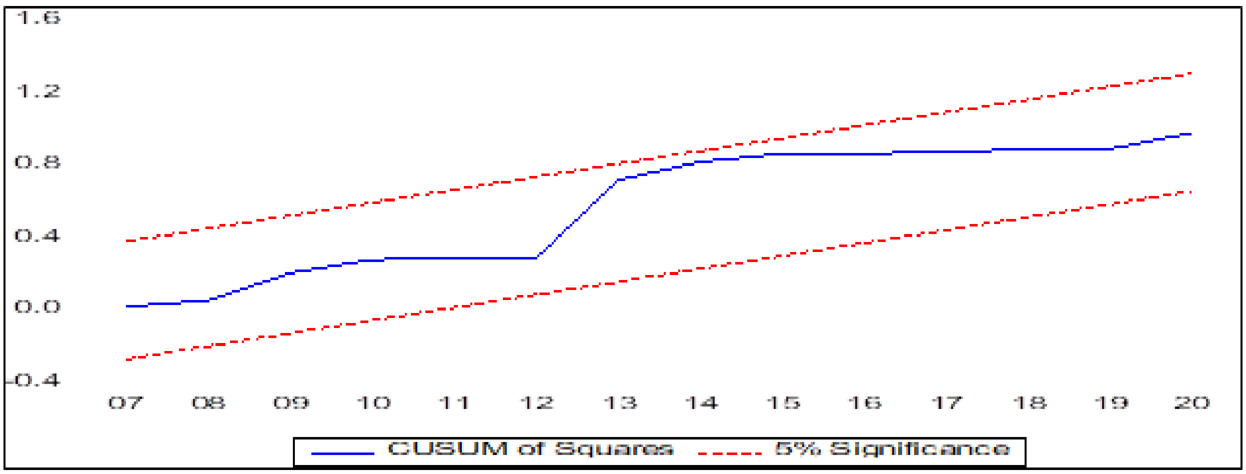


Figure 2: Graph of the cumulative sum of squares (CUSUMQ) of recursive residuals. Red lines indicate the upper and lower critical interval at a 5% level of significance



Residual Diagnostics

Table 7: Residual Diagnostics

Test for	Diagnostic Test	p values	Conclusion
Serial correlation	Breusch–Godfrey LM Test	1.8093 (0.2057)	No Serial correlation
Heteroscedasticity	Breusch–Pagan–Godfrey Test	1.2904 (0.3204)	No Heteroskedasticity
Normality	Jarque–Bera Test	0.6530 (0.7214)	Normal distribution
Goodness of Fit	R-Square Test	0.8794 (0.0002)	The model has a good fit

It can be seen that the p-value for the Jarque Bera Statistics is well above 5%, telling us that the data more likely proceeds from a normal distribution. It is important to ensure that model residuals are normally distributed to avoid spurious regressions (Greene, 2002). Given that the p-value is well above 5% for the Breusch–Pagan–Godfrey Test, this tells us that we cannot reject the null hypothesis of homoscedasticity. Implying the residuals are not heteroskedasticity. Further, we also find evidence that the residuals are not serially correlated. As discussed before model fits well the data.

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CONCLUSION AND POLICY RECOMMENDATION

In this study, the aim was to examine the asymmetric impacts of sectoral growth (i.e., growth size effect) and different sectoral growth patterns (i.e., growth composition effect) on the unemployment rate in Uganda during the period 1980-2020 by applying the nonlinear NARDL model. The NARDL model helped to identify both short-run (i.e., adjusting) and long-run (i.e., cointegrating) dynamics that link Uganda's sectoral growth to its unemployment rate.

One of the major concerns of developing countries like Uganda is persistent unemployment rates amidst reported sustained growth. The main question of concern in this study was why is unemployment in Uganda not responsive to economic growth. The current study tries to answer this question by examining the linkage between unemployment and sectoral growth patterns considering both the size of growth and the composition of growth (i.e., as proxied by sectoral labour intensity). Given that shocks to different sectors are associated with different impacts on unemployment, the study used a nonlinear ARDL model to examine the asymmetric impact of growth size and growth composition of sectors on unemployment in Uganda.

Considering the size of sectoral growth, it was found that a 1% positive and negative shock to agricultural value-added annual growth has a negative and positive association with unemployment. However, the effect is not significant. Similarly, although not significant, a 1% positive shock in the industrial value-added annual growth has a positive relationship with unemployment. While a similar but negative shock is associated with a reduction in the unemployment rate. This is a surprising finding, first until recently most of the industrial products especially construction products were imported implying growth in the industrial value would include imported goods that do not create employment during their production process. Secondly, most of the industries in Uganda are owned by foreigners mainly the Chinese and Indians who import their labour denying Ugandans employment. In this case, a positive shock to the industrial sector will not result in a tangible reduction in the unemployment rate in the country. Thirdly industrial establishment also requires large initial capital to set up thus a favourable shock amidst capital constraints will not have any impact on unemployment in Uganda. This could explain the stagnant growth of the industrial sector in the last three decades in Uganda, contributing less than a quarter of total employment in the country. Lastly, it was found that a 1% positive shock to the value added to the services significantly lowered the unemployment rate. With the recent rapid growth in ICT services, the services sector growth can rapidly adjust to respond to a positive shock in the services sector growth, unlike other agriculture and industrial sectors which may drag to adjust during a positive shock in the sector. The asymmetric nature of sectoral growth implies the size of sectoral growth matters for unemployment reduction.

Results from the composition effect of growth indicate that it is not only the size of sectoral growth that matters for unemployment reduction but also how the growth is composed in terms of sectoral patterns of growth also matters for the unemployment rate reduction. Given the results of this study, addressing the unemployment process should continue to be a top development priority for the government focusing both on the size of the economy and the composition of growth if the government is to achieve any of its short-term, medium term and long term growth targets as emphasized in the national development plan (NDP III) and also in the Uganda vision 2040. Government must integrate the impact of both positive and negative shocks in the formulation of unemployment reduction policies.

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The government should consider integrating unemployment measures concerning both the projected size of overall growth and the composition of this growth in both the national planning and budgeting frameworks. In addition, measures of employment generation performance concerning sectoral growth should be tracked and monitored annually and also included in national planning and budgeting frameworks. Sectoral resource allocation during the budgeting phase should follow sectoral employability performance indicators such that more labour-intensive sectors are allocated more resources to create more jobs. Government should also rebalance its sectoral growth planning to reduce excess labour being trapped in underpaying sectors such as subsistence agriculture. Further, there should be a mechanism to rethink and overhaul the traditional government employment creation strategies by designing and implementing an employment strategy that is integrated at the national level to ensure value for money in the employment creation sector. The government of Uganda should harmonize and evaluate employment generation programs before launching new ones. In Uganda, employment creation programs are not based on sectoral growth projections, instead, they are politically motivated, uncoordinated, and not mainstreamed in the national planning frameworks. Such programs are characterized by leakages and create windfall employment which can mislead planning.

REFERENCES

Alvarez-Cuadrado, F., & Poschke, M. (2011). Structural change out of agriculture: Labour push versus labour pull. *American Economic Journal: Macroeconomics*, *3*(3), 127–158. https://doi.org/10.1257/mac.3.3.127

Arias-Vazquez, J. F., Lee, J., & Newhouse, D. (2021). The Role of Sectoral Growth Patterns in Labour Market Development. *SSRN Electronic Journal*, *6926*. https://doi.org/10.2139/ssrn.2164655

Baltagi, B. H. (2021). *Econometric Analysis of Panel Data* (sixth). Springer. http://www.springer.com/series/10099

Basile, R., Girardi, A., Mantuano, M., & Pastore, F. (2011). Sectoral shifts, diversification and regional unemployment: Evidence from local labour systems in Italy. *Empirica*, *39*(4), 525–544. https://doi.org/10.1007/s10663-012-9198-3

Bwire, T., Asiimwe, W., Tinyinondi, Grace, A., Kisakye, P., & M. Ayume, D. (2016). *Private and Public Investments and Economic Growth in Uganda: A Multiplier Model Analysis* (Issue 01).

Byiers, B., Takeuchi, L. R., Rosengren, A., Muhwezi, M., Turyareeba, D., Abaliwano, J., Wabukala, B., & Ggoobi, R. (2015). *Work in progress Productive employment and transformation in Uganda*. *March*.

Caselli, F., & Michaels, G. (2009). Do Oil Windfalls Improve Living Standards? Evidence From Brazil. In *Economics, American Economic Association: Vol. 5(1)*. http://www.nber.org/papers/w15550

Cho, J. S., Greenwood-Nimmo, M., & Shin, Y. (2019). *Two-Step Estimation of the Nonlinear Autoregressive Distributed Lag Model*. *2019*rwp-*154*, 1–44. https://ideas.repec.org/p/yon/wpaper/2019rwp-154.html

Cho, J. S., Greenwood-Nimmo, M., & Shin, Y. (2021). Recent developments of the autoregressive distributed lag modelling framework. *Journal of Economic Surveys*, 1–26. https://doi.org/10.1111/joes.12450

Christiaensen, L., Demery, L., & Kuhl, J. (2010). The (Evolving) Role of Agriculture in Poverty Reduction. In *UNU-WIDER Working Paper 2010* (Vol. 36).

Article DOI: https://doi.org/10.37284/eajbe.6.1.1120

Christiaensen, L., & Kaminski, J. (2015). Structural Change, Economic Growth and Poverty Reduction, Micro Evidence From Uganda. *African Development Bank Group Working Paper*, *229*(229). http:/www.afdb.org/

de Janvry, A., & Sadoulet, E. (2009). *The Quality of Growth and Poverty Reduction in China* (Vol. 38, Issue 4). http://linkinghub.elsevier.com/retrieve/pii/S0305750X08000107%5Cnhttp://www.ncbi.nlm.nih.gov/pubmed/12294267%5Cnhttp://www.nber.org/papers/w18100%5Cnhttp://linkinghub.elsevier.com/retrieve/pii/S0305750X03001682%5Cnhttp://link.springer.com/10.1007/978-3-64

Ellis, M., McMillan, M., & Silver, J. (2018). Employment and Productivity Growth in Tanzania ' s Service Sector 2 . Employment and Productivity Growth in Services : The Big Picture.

Feder, G. (1982). On Export and Economic Growth. *Journal of Development Economics*, *2*, 59–73.

Gemmell, N. (1982). Economic Development and Structural Change: The Role of the Service Sector. *The Journal of Development Studies*, *19*(1), 37–66. https://doi.org/10.1080/00220388208421849

Ggoobi, R., Wabukala, B. M., & Joseph, N. (2017). Economic development and industrial policy in Ugnada. In *Applied Geography*. https://doi.org/10.1016/0143-6228(95)90025-x

Gicharu, S. M., & Muturi, W. (2021). Determinants of Unemployment in East African Community Countries. *Account and Financial Management Journal*, *06*(10), 2526–2537. https://doi.org/10.47191/afmj/v6i10.06

Greene, W. (2002). *Econometrics Analysis* (Fifth).

Guloba, M. M., Kakuru, M., & Ssewanyana, S. N. R. J. (2022). Employment creation potential, labour skills requirements and skill gaps for young people A Rwanda case study Employment creation potential, labour skills requirements, and skill gaps for young people: A Rwanda case study. February.

Lewis, W. (1954). *Economic Development with Unlimited Supplies of Labour*. *30*(2), 169–169. https://doi.org/10.1111/j.1813-6982.1962.tb02428.x

Lilien, D. M. (1982). Sectoral Shifts and Cyclical Unemployment. *Journal of Political Economy*, *90*(4), 777–793. https://www.jstor.org/stable/1831352

Liu, Y., Zhang, Q., Liu, Q., Yan, Y., Hei, W., Yu, D., & Wu, J. (2020). Different household livelihood strategies and influencing factors in the inner Mongolian Grassland. *Sustainability (Switzerland)*, *12*(3). https://doi.org/10.3390/su12030839

Loayza, N., & Raddatz, C. (2006). The Composition Of Growth Matters For Poverty Alleviation.

Matovu, J. M. (2000). Composition of Government Expenditure, Human Capital Accumulation, and Welfare. *International Monetary Fund*.

Mcmillan, M. S., & Rodrik, D. (2011). Globalization, Structural Change And Productivity Growth.

Merotto, D. (2019). Uganda Jobs Strategy for Inclusive Growth. In *Documents.Worldbank.Org* (Issue 19). https://documents.worldbank.org/curated/en/693101582561426416/pdf/Uganda-Jobs-Strategy-for-Inclusive-Growth.pdf

Mugisha, M. B., & Kitamirike, E. (2017). Two Decades of Growth with Limited Job Creation : What Explains Uganda ' s Economic Growth Paradox ? 1. *Journal of African Democracy and Development*, *1*(2), 70–93.

Article DOI: https://doi.org/10.37284/eajbe.6.1.1120

Mukisa, I., Nathan, S., & Bulime, E. W. N. (2020). Macroeconomic Determinants of Unemployment In the East African Community. *Tanzanian Economic Review*, *10*(2), 48–68.

NDP II (2015/16 – 2019/20). (n.d.). Second National Development Plan. In *National Planning Authority Uganda* (Vol. 1, Issue 2). http://npa.ug/wp-content/uploads/NDPII-Final.pdf

Noland, M., Park, D., & Estrada, G. B. (2012). Developing the Service Sector as Engine of Growth for Asia: An Overview (Issue 320).

Pesaran, M. H., & Shin, Y. (1998). *An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis* (Issue February). https://doi.org/10.1017/ccol0521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. j. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, *326*(February), 289–326. https://doi.org/10.1002/jae.616

Pissarides, C. A. (1998). The impact of employment tax cuts on unemployment and wages; The role of unemployment benefits and tax structure. *European Economic Review*, *42*(1), 155–183. http://search.proquest.com/docview/198056851/abstract

Ravallion, M., & Chen, S. (2004). China' s (Uneven) Progress Against Poverty. *World Bank Policy Research Working Paper*, *3408*, 1–57.

Ravallion, M., & Datt, G. (1996). How important to India's poor is the sectoral composition of economic growth? *World Bank Economic Review*, *10*(1), 1–25. https://doi.org/10.1093/wber/10.1.1

Ravallion, M., & Datt, G. (2001). Why has economic growth been more pro-poor in some states of India than others? *Journal of Development Economics*, *68*(2), 381–400. https://doi.org/10.1016/S0304-3878(02)00018-4

Sharma, R., & Singh, G. (2019). Livelihood diversification strategy and technology access in rural India. *Agriculture Innovation Systems in Asia*, *September*, 206–229. https://doi.org/10.4324/9780429264092-10

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. *SSRN Electronic Journal*, *44*(0), 1–44. https://doi.org/10.2139/ssrn.1807745

Shinyekwa, I., Kiiza, J., Hisali, E., & Obwona, M. (2016). The Evolution of Industry in Uganda. In *Manufacturing Transformation* (Issue 9). https://doi.org/10.1093/acprof:oso/9780198776987.003.0010

Ssewanyana, S., Matovu, J. M., & Twimukye, E. (2011). Building on Growth in Uganda. In *World Bank* (p. 51).

Suryahadi, A., Suryadarma, D., & Sumarto, S. (2008). The effects of location and sectoral components of economic growth on poverty: Evidence from Indonesia. *Journal of Development Economics*, *89*(1), 109–117. https://doi.org/10.1016/j.jdeveco.2008.08.003

Syrquin, M., & Chenery, H. B. (1989). *Patterns of development, 1950 to 1983* (Issue March). https://documents1.worldbank.org/curated/en/427771468739525450/pdf/multi-page.pdf

UBOS. (2020). *The Economic Performance of Uganda' S Economy in FY 2019 / 20* (Vol. 256, Issue June). Uganda Bereau of Statistics. www.ubos.org

Woolridge, J. (2000). Introductory Econometrics, A modern Aproach (third).

Article DOI: https://doi.org/10.37284/eajbe.6.1.1120

World Bank. (2020). UGANDA Economic Update, Strengthening Social Protection to Reduce Vulnerability and Promote Inclusive Growth. In *Africa Research Bulletin: Economic, Financial and Technical Series* (Vol. 58, Issue 5). https://doi.org/10.1111/j.1467-6346.2021.10068.x

