Electricity Availability, Electricity Prices and Growth of Uganda's Industrial Sector: A causality and shock impact analysis

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Abstract

Evidence suggests that a well-developed and sound industrial sector plays a pivotal role in the economic development of nations. Given this empirical stance, the realization of sustainable growth trajectories for developing countries, Uganda in particular, requires policymakers to understand the causal relationships and assess how industrial sector output growth responds to sudden changes in its stimulus factors in a dynamic setting. This study investigated the causality relationships and assessed shock effects between electricity availability, electricity prices, and industrial sector performance in Uganda. Utilizing quarterly time-series secondary data for the period 2009–2024, the study estimated a Structural Vector Auto Regression with exogenous regressors (SVARX), employing Wald Granger causality tests and assessing impulse response functions (IRFs). The causality results reveal bidirectional causality between industrial sector output and both electricity access and consumption. Unidirectional causality runs from electricity installed capacity and supply volatility to industrial sector output, while no causality exists between industrial electricity prices and output. Furthermore, shocks to electricity supply volatility and consumption have asymmetric effects that die out by the eighth quarter, whereas shocks to installed capacity, access, and prices trigger asymmetric positive and negative impacts that persist beyond the eight-quarter period. Deliberate policy should cushion these factors against shocks for robust, sustainable industrial growth.

Keywords: Electricity availability, industrial electricity prices, Industrial Sector output, Causality, Uganda.

JEL classification codes: Q43; O14; L94; C32

توفر الكهرباء، وأسعار الكهرباء، ونمو القطاع الصناعي في أوغندا: تحليل السببية وأثر الصدمات

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الملخص:

تشير الأدلة إلى أن وجود قطاع صناعي متطور وسليم يؤدي دوراً محورياً في التنمية الاقتصادية للأمم. وبناءً على هذا الموقف التجريبي، فإن تحقيق مسارات نمو مستدام للدول النامية، ولا سيما أوغندا، يتطلب من صناع السياسات فهم العلاقات السببية وتقييم كيفية استجابة نمو إنتاج القطاع الصناعي للتغيرات المفاجئة في عوامله التحفيزية في بيئة ديناميكية. تناولت هذه الدراسة تقصي علاقات السببية وتقييم آثار الصدمات بين توفر الكهرباء، وأسعار الكهرباء، وأداء القطاع الصناعي في أوغندا. وباستخدام بيانات ثانوية لسلاسل زمنية ربع سنوية للفترة الممتدة بين عامي 2009 و2024، قدرت الدراسة نموذج الانحدار الذاتي الموجه الهيكلي مع متغيرات مفسرة خارجية (SVARX)، مع تطبيق اختبارات "والد" لسببية "جرانجر"، وتقييم دالات الاستجابة للنبضة (IRFs).تظهر نتائج السببية وجود سببية ثنائية الاتجاه بين إنتاج القطاع الصناعي وكل من الوصول إلى الكهرباء واستهلاكها. وفي المقابل، تتجه السببية أحادية الاتجاه من القدرة الكهربائية المركبة وتقلبات إمدادات الكهرباء إلى إنتاج القطاع الصناعي، في حين لا توجد علاقة سببية بين أسعار الكهرباء الصناعية وإنتاج القطاع. وعلاوة على ذلك، تبين أن الصدمات الموجّهة لتقلبات إمدادات الكهرباء واستهلاكها تخلف آثاراً غير متماثلة تتلاشى بحلول الربع الثامن، بينما تؤدي الصدمات الموجّهة للقدرة المركبة، والوصول إلى الكهرباء، والأسعار، إلى إحداث تأثيرات إيجابية وسلبية غير متماثلة تستمر لما بعد فترة الفصول الثمانية. وبناءً على ذلك، ينبغي توجيه سياسات مدروسة لحماية هذه العوامل ضد الصدمات لضمان تحقيق نمو صناعي قوي ومستدام.

الكلمات المفتاحية: توفر الكهرباء، أسعار الكهرباء الصناعية، مخرجات القطاع الصناعي، السببية، أوغندا.

تصنيف JEL: Q43; O14; L94; C32

1. Introduction

A well developed and sound industrial sector plays a central role in economic development of a nation (Banerjee et al., 2020). The nation's industrialization process involves a movement from the economy's dominance on agricultural output and employment to the one dominated by manufacturing (Muwanguzi et al., 2018). In this process, the nation begins to establish factories that turn raw materials into finished products for final human and non-human consumption. The historical strategic economic importance of the industrial sector can be traced from the fact that, as economies transitioned from subsistence agricultural production towards higher value manufacturing, service and agro-processing activities, the industries offered higher value addition and more productive jobs that drove long term improvements in living standards (Leipziger & Manwaring, 2020). In support of the central role of industrial sector growth to modern civilization, development plan followed the earlier five-year development plan of 1962-1966 which had focused on agricultural development. The 196-1971 development had the same goals consistent with the views of the Economic Commission for Africa (ECA) which was held in Zambia in 1965 which recommended the need for industrialization and economic transformation in the whole of eastern Africa, with priorities including the textile, wood and cork, rubber products, and iron and steel industries (United Nations Economic Commission for Africa, 2017). Such development initiative set Uganda registering rising manufacturing output, but which was short lived, until the ushering in of the development crisis in the 1970s due to political instabilities that led to destruction of the economy and disorganized industrial infrastructure. The availability of cheap labour and the high cost of imported technology around this time meant that light industries were the available starting points on the path to Aiginger & Rodrik (2020) and Mountjoy (2017) state that every economy in the world is recognized to have achieved overall economic growth through investing in the industrial sector.

The struggle for a lucrative industrialization agenda for Uganda began with the second five-year development plan of 1967-1971 which focused on value added manufacturing. This five-year industrialization. More recently however, Uganda is seen to have stepped up efforts to position the industrial sector at the center of her development agenda. Uganda's stance to development of her industrial sector is for instance visibly reflected in her National Industrial Policy 2020 which is the most recent framework designed to guide Uganda's Industrialization process and spur Uganda's industrial development and in Uganda's vision 2040 which highlights the importance of industrialization and value addition to achieve Uganda's dream of transforming Ugandan society from a predominantly peasant and low-income society to a competitive upper-middle-income country within 30 years.

Despite Uganda's strong emphasis to development of her industrial sector, the country continues to export largely-unprocessed primary products and the share contribution of industrial output in Uganda's overall Gross Domestic Product continue to be dismal. For instance Uganda's industrial sector output contributed 24.9 percent total GDP in financial year 2023/2024 (UBOS, 2023), which showed a decline from 25.4 percent in the previous financial year 2022/2023 and from 26.8 percent in the previous financial year but one 2021/2022. When it comes to the industrial sector's contribution in total employment, only 7.2 percent of Uganda's working population are employed in the industrial sector (UBOS, 2023). Whereas this is the case for industrial sector performance, Uganda's electricity sub-sector are not appealing either. For instance, statistics indicate that Uganda's total installed capacity of electricity power sources was 1,778.1 MW in the year 2022 (UBOS, 2023) standing much lower than that of African's power house South Africa of 63,400 MW in the same year; Uganda's total quantity of electricity generated stood at only 5, 211 GWh in the year 2022 which, in comparison, was much lower than that of Africa's power house South Africa whose total quantity power generation stood at *234,850* GWh in the same year; load shedding (which serves an indicator of electricity supply reliability) for electricity end users was estimated at an average of three times a week for about 18 hours a day in the year 2021 (UBOS, 2022) and electricity consumption per capita for Uganda was estimated at 83.5 kWh in the year 2022 (UBOS, 2023) which is much lower than Africa's per capita electricity consumption of 632kWh (IEA, 2023). The observed Ugandan case is that not only does Uganda's industrial output represent a small share in her total GDP but also records poor electricity sub-sector indicators.

While offering diverse conceptualizations on what constitutes electricity availability, a review of related studies done on Uganda in the empirical literature indicated that authors have predominantly investigated the link between at most one indicator of electricity availability on overall growth in GDP, with a larger number of studies linking electricity consumption to growth in GDP and a smaller number of studies linking electricity consumption to industrial sector growth and a much smaller number of studies which have investigated the link between electricity availability, electricity prices and growth of industrial output. Consequently, the relationship between the various dimensions of electricity availability, electricity prices and growth of the industrial sector output is not well understood in the context of Uganda. The purpose of this study therefore is to conduct an empirical investigation of the causality relationships and assess shock effects between electricity availability, electricity prices and industrial sector performance in Uganda. Particularly, the study investigates the causality relationships between four dimensions electricity availability as defined by Rohan & Burke (2018) (i.e. electricity generation capacity, the quality of electricity produced, the quantity of electricity consumed and the electricity access rate), industrial electricity prices and industrial sector output, using time series quarterly data on Uganda.

Identifying the causality relationships between electricity availability, electricity prices and the industrial output growth is particularly important for the policy makers to understand which particular policy variables to regulate and which industry stimulating factors to cushion in the face of shocks in the economy, with the overall aim of enabling sustained economic growth of the country. For instance in line with arguments by Yoo and Kim (2006), one-way causality running say from electricity generation to industrial sector output growth would imply enactment of policies in favour of more electricity generation targeting the industrial sector; one-way causality running from industrial sector output growth to electricity generation would imply policies to reduce electricity to the industrial sector could be made without affecting the industrial sector's output growth; and no causality would imply that electricity generation to the industrial sector could be reduced without affecting the industrial sector's output growth. Investigation of the causality relationships between the various dimensions of electricity availability as well as electricity prices on industrial sector output growth and to assess the shock impacts in order to ensure stable, sufficient and affordable electricity necessary for development of the industrial sector and fostering the overall economic growth and development.

2. A Literature Survey

A related study on Uganda was conducted by Akankunda et al. (2022) who examined the effect of electricity consumption, capital, labour and education on industrial output in Uganda. The study utilized a 10-year period time series data for the period 2009-2019. The study estimated a vector error correction model (VECM) to determine the long-term relationship between industrial output and its explanatory variables. The study used electricity consumption, Education, labour and capital as the key study independent variables, and industrial output was used as the dependent variable. The study results found strong evidence that electricity consumption, labour employed and industrial output were positively correlated, and that education, electricity consumption and labour had a long-term causality on industrial output. It is worth to note that whereas the study by by Akankunda et al. (2022) examined the same outcome variable as the current study (Industrial output), the variables examined and the study purpose are somewhat different. But also, methodologically, the two studies differ in terms of estimation techniques: Whereas the study by Akankunda et al. (2022) employed VECM framework for estimation, the current study to employs the SVARX estimation framework. Additionally, the study by Akankunda et al. (2022) utilized low frequency data based on annual series and for rather a shorter period (i.e. 2009-2019). The current study however utilized high frequency data based on quarterly series for a quite longer time span (i.e. 2009-2024).

Using quarterly time series data for the period 2008-2018, a related study by Mutumba et al. (2023) examined the causal relationship between electricity consumption and economic growth for Uganda. The study included additional variables, namely real fixed capital formation and labour force in the GDP - Electricity Consumption Model. The vector error correction model (VECM) was employed to examine the causal relationships in the empirical model, and granger causality test was employed to examine the direction of causality. Results from the study indicated a bidirectional causality between electricity consumption and economic growth in both the short run and long run. Whereas in Mutumba et al. (2023) study targeted the overall growth in GDP as the dependent variable, in the current study the industrial output has been used as one of the endogenous variables. Secondly, the study by Mutumba et al. (2023) examined one of the indicators of electricity availability (i.e. electricity consumption) while the current study examines four components of electricity availability.

In another related study done on Uganda by Mawejje and Mawejje (2016) examined the causal relationship between electricity consumption and sectoral output growth using quarterly time series data for the period spanning from 2005q1 to 2015q1. The study exploited the vector error correction modelling (VECM) framework and the granger causality tests to investigate the causality relationship between the underlying variables and the direction of causality respectively. Results suggested that there was a unidirectional long-run causal relationship running from electricity consumption to GDP. Unlike the current study which examines causality relationships between more than one component of electricity availability and the industrial sector output, the study by Mawejje and Mawejje (2016) examined the causality between one of the components of electricity availability, i.e. electricity consumption and sectoral output growth . However, a key credit identified in the study by Mawejje and Mawejje (2016) is the ability to utilize high frequency data (as also have been done in the current study) and also examining electricity consumption effects on outputs of various economic sectors. However, again, different from the study by Mawejje and Mawejje (2016), the current study estimates employs the granger causality test after estimating an SVARX model and goes ahead to estimates and examine impulse response functions and forecast error variance decompositions.

A study by Alinaitwe (2023) on Uganda examined the short-run and long-run relationships between electricity consumption and economic growth in Uganda while controlling for additional economic growth factors such as inflation, population growth, trade openness and government consumption. The study used quarterly data from 2008Q1-2021Q3. The author used the Philips Peron approach to test for stationarity and employed the Auto Regressive Distributed Lag (ARDL) approach to estimate the underlying relationship. The study found cointegration between logarithm of GDP and its determinants and Logarithm of electricity consumption and its determinants. Like it was in the study by Mutumba et al. (2023), results from the study by Alinaitwe (2023) showed evidence of feedback hypothesis between electricity consumption and economic growth for Uganda. As much as Alinaitwe's (2023) study utilized high frequency data, examined long run and short run relationships, is done in the current study, the deviating features of the current study from the study by Alinaitwe (2023 are: the current study examines electricity supply quality as one of the endogenous variables in the SVARX model, the current study's dependent variable is industrial sector output, and the current study examines data for a wider time span, but also the current study examines impulse responses and forecast error variance decompositions which are useful in identifying a more precise direction of policy action.

Another related study to the current research was conducted by Okoboi and Mawejje (2016) whose study focused on examining the trends as well as forecasting of the medium term path of electricity peak demand in Uganda. The study used a descriptive research design and augmented it by empirical estimations of structural break equations in order to account for the observed trends in electricity peak demand in Uganda. The study also applied the double exponential forecasting model to forecast total peak electricity demand. Findings of the study were that Uganda's surge in electricity peak demand was due to increased electricity exports. Unlike the current study which examines causality relationships, the study by Okoboi and Mawejje (2016) adopted the descriptive research design to the study variables. Thus the study by Okoboi and Mawejje (2016) was limited to descriptive analysis while the current study offers a wider analyses involving investigation of direction of causality relationships between the study variables and assessment of impulse response functions and forecast error variance decomposition.

Using pseudo panel data from a selected sample of Ugandan manufacturing firms, Aggrey and Ogwal (2013) investigated the effects of investment climate on manufacturing firms' output growth in Uganda. More specifically, the study analyzed investment climate factors from the side of firm characteristics that determine firm growth in Uganda. The study adopted the Gibrats Law of Proportionate Effect (LPE) and Learning model with some modifications in the analysis. Results from the study showed that factors such as firm size, age of the firm, and average education of firm managers are the main determinants of growth in a sample of Ugandan manufacturing firms. The study reported that the other firm level characteristics such as Access to credit, value added capital ratio, and unionization were shown to have a negative and weak association with firm growth. In addition, the study found that variables such as gender, sector effects, export participation, inadequate provision of infrastructure, inadequate demand for produced products, location in the city, foreign ownership, and education of the manager and loss of output due to power outages had the expected signs but their respective coefficients were not statistically significant. It is worthy to note the study by Aggrey and Ogwal (2013) and the current study focus on different sets of study purposes, notably, the purpose of the current study is to examine causality relationships between electricity availability, electricity prices and industrial sector output whereas the study by Aggrey and Ogwal (2013) aimed at investigating the effects of investment climate on manufacturing firms' output growth.

Elsewhere, a closely related study was launched by Khobai et al. (2017) who investigated a causal relationship between electricity supply and economic growth in South Africa using annual data for the period from 1985 to 2014 using the Vector Error Correction Model (VECM) for directional causality analysis and the Autoregressive Distributed Lag (ARDL) model for long run causality estimations. The results from the Khobai et al. (2017) study revealed bidirectional causality running between electricity supply and economic growth. Another closely related study was launched by Rohan and Burke (2018) who investigated the question of if greater electricity availability helps countries ascend to faster economic growth trajectories using annual data for the period 2006-2016 on a cross sectional of a sample of developing countries and the rest of the broader diaspora of countries. The study by Rohan and Burke (2018) found that greater electricity availability had a significant effect on subsequent economic growth, though much of the effect disappeared with inclusion of suitable control variables in the regression. Husaini and Lean (2015) investigated the relationship between electricity consumption, electricity prices and the manufacturing sector output in Malaysia by employing the unrestricted error correction model (UECM) via the ordinary least squares (OLS). Findings from the study revealed that (i) there was a unidirectional causality from manufacturing output to electricity consumption in the long run, and (ii) there was a unidirectional causality from electricity consumption to output in the short run. Using annual data for the period 1960–2008, Jamil and Ahmed (2010) analyzed the causality relationship between electricity consumption and real GDP in Pakistan while including electricity prices as control variable in the empirical model. Analysis was done at both aggregate and sectoral levels. The study employed a vector auto regression approach (VAR), and findings from the study that there was unidirectional causality from real economic activity to electricity consumption. Aneja and Mathpal (2022) examined the long-run causal link as well as causality relationship between the per capita electricity consumption, per capita gross domestic product, urban population and employment pattern in India over the period of 1991–2018. The study by Aneja and Mathpal (2022) employed the Johansen co-integration test and the Granger-causality using the Vector error correction (VECM) analytical procedures to achieve the study objectives, and findings from the study showed a bidirectional causal relationship between the per capita electricity consumption and per capita gross domestic product whereas was a unidirectional causality from employment and urban population to per capita gross domestic product. Another related study was conducted by Apaydin et al. (2019) who analyzed the asymmetric effects of renewable energy consumption on economic growth in Turkey using a nonlinear autoregressive distributed lag (NARDL) model, and the study reported asymmetric shock effects: positive and negative shocks in renewable energy consumption on economic growth. A study by Zhong et al. (2019) which investigated the relationship between electricity consumption, economic growth and employment in China during the period of 1971-2009 by employing the autoregressive distributed lag (ARDL) bounds testing approach revealed that there was existence of a unidirectional short-run and long-run causalities from electricity consumption and employment to economic growth and that electricity served as an important driver of economic growth.

3. Methods and materials

The study utilizes quarterly time series secondary data for the period 2009-2024. The data was obtained from the Electricity Regulatory Authority (ERA) of Uganda and Bank of Uganda (BoU). Prior to causality analysis, the study conducts the conventional pre-estimation diagnostic tests to time series multiple linear regressions, namely the unit root test using the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and the cointegration test using the Johansen (1995) test. Assessment of the of causality relationships is achieved by first estimating a Structural Vector Auto Regression with exogenous regressors (SVARX) (as for instance in Hamilton, 1994) and then employing the Wald granger causality tests. Shock impact assessment is done by estimating and assessing the impulse response functions (IRFs) after SVARX estimation.

The study proceeds as follows in the development and specification of the analytical models:

Consider a VARX where there are K-variables each of which is a function of their own p-lags and p-lags of other (K-1) variables as well other exogenous variables, henceforth VARX:

3.1 Descriptive statistics and preliminary analysis

Initial inspection of the monthly sales series for BTM and BTMP (Figure 1) showed clear cyclicality consistent with the operational patterns of the construction and public works sectors in Algeria. Bitumen demand typically escalates during the warmer, drier months optimal for asphalt paving, producing a distinct seasonal pattern within each year.

$$y_t = v + A_1 y_{t-1} + \cdots + A_1 y_{t-p} + B_0 x_t + B_1 x_{t-1} \ldots + B_s x_{t-s} + u_t \quad (1);$$

where $y_t = (y_{1t}, \ldots, y_{Kt})'$ is a K x 1 random vector of endogenous variables, $A_1, \ldots A_p$, are K x K matrices of parameters, x_t is an M x 1 vector of exogenous variables, $B_0, \ldots, B_s$ are K x M matrices of coefficients, v is a K x 1 vector of parameters, and u_t is assumed to be white noise such that : $E(u_t) = 0, E(u_t u_t') = \Sigma$ and $E(u_t u_s') = 0$. The cross-equation error variance–covariance matrix, Σ contains all the information about contemporaneous correlations in a typical VAR model and this in fact an inherent strength of a VAR.

It should be noted that there are no assumption imposed in the specification of the VARX in (1). If at all certain technical assumptions are imposed and assuming that the VAR is stable, we can derive another presentation of the VARX in (1) called the vector moving-average representation of the VARX as:

$$y_t = \mu + \sum_{i=0}^{\infty} D_i\, x_{t-i} + \sum_{i=0}^{\infty} \Phi_i\, u_{t-i} \qquad (2);$$

where: where μ is the K x 1 time-invariant mean of the process and D and Φ are K xM and K x K matrices of parameters, respectively. The vector moving-average representation of the VARX in (1) states that the process by which the variables in y_t fluctuate about their time-invariant means, μ, is completely determined by the parameters in D and Φ, and the infinite past history of the exogenous variables x_t and the independent and identically distributed (i.i.d.) shocks or innovations, $u_{t-1}, u_{t-2}, \ldots$. The moving-average coefficients Φ_i are also known as the simple IRFs at horizon, i.

The only remaining problem with utilization of (1) and (2) for shock analysis is that because Σ is not restricted to be a diagonal matrix, no causal interpretation of the simple IRFs is possible. To rectify this concern, let a matrix P be such that: $\Sigma = \mathrm{PP}'$. The matrix P can be chosen using Sims (1980) approach of Cholesky decomposition of $\hat{\Sigma}$ where the IRFs based on this choice of P are known as the orthogonalized IRFs. After choosing matrix, P, the variables in $\mathrm{P}^{-1}u_t$ is will have a zero mean and that $E[\mathrm{P}^{-1}u_t(\mathrm{P}^{-1}u_t)'] = I_K$. We could then write (2) as:

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_s\, PP^{-1}u_{t-s} = + \sum_{i=0}^{\infty} \Theta_s\, P^{-1}u_{t-s} \qquad (3);$$

where: $\Theta_s = \Phi_s P$. Equation (3) is the SVARX model. The SVARX in (3) would allow the causal interpretation of simple IRFs that we are interested in. The estimated P matrices are the ones used to estimate structural IRFs and structural FEVDs in both short-run SVARX and in the long-run SVARX. The short-run SVARX models identify a P matrix by placing restrictions on the contemporaneous correlations between the variables while the long-run SVARX models do so by placing restrictions on the long-term accumulated effects of the innovations.

Using the variable notations adopted in this study, the SVARX for empirical analysis is specified as:

$$\begin{aligned} Ind\_y_t = \beta_{10} &+ \sum_{i=1}^{m} \beta_{1i}\, Ind\_y_{t-i} + \sum_{j=1}^{m} \beta_{1j}\, gkf_{t-j} + \sum_{k=1}^{m} \beta_{1k} elec\_avail_{t-k} \\ &+ \sum_{l=1}^{m} \beta_{1l} ind\_\mathrm{tariff}price_{t-l} + \pi_{11} ind\_lbr_t + \pi_{12} fdi_t + \pi_{13} indcredit_t + u_t \end{aligned}$$

(4a)

$$\begin{aligned} \overrightarrow{elec\_avail}_t = \beta_{20} & \\ &+ \sum_{i=1}^{m} \beta_{2i}\, elec\_avail_{t-i} + \sum_{j=1}^{m} \beta_{2j}\, Ind\_y_{t-j} + \sum_{k=1}^{m} \beta_{2k} gkf_{t-k} \\ &+ \sum_{l=1}^{m} \beta_{2l} ind\_tariffprice_{t-l} + \pi_{21} ind\_lbr_t + \pi_{22} fdi_t + \pi_{23} indcredit_t + \varepsilon_t \end{aligned}$$

(4b)

$$ind\_tariffprice_t = \beta_{30} + \sum_{i=1}^{m} \beta_{3i}\, \mathrm{ind}\_tariffprice_{t-i} + \sum_{j=1}^{m} \beta_{3j}\, Ind\_y_{t-j} + \sum_{k=1}^{m} \beta_{3k} gkf_{t-k} + \sum_{l=1}^{m} \beta_{3l} elect\_avail_{t-l} + \pi_{31} ind\_lbr_t + \pi_{32} fdi_t + \pi_{33} indcredit_t + e_t$$

(4c)

$$gkf_t = \beta_{40} + \sum_{i=1}^{m} \beta_{4i}\, gkf_{t-i} + \sum_{j=1}^{m} \beta_{4j}\, Ind\_y_{t-j} + \sum_{k=1}^{m} \beta_{4k} elec\_avail_{t-k} + \sum_{l=1}^{m} \beta_{4l} ind\_tariffprice_{t-l} + \pi_{41} ind\_lbr_t + \pi_{42} fdi_t + \pi_{43} indcredit_t + z_t \quad (4d);$$

where in (4a)-(4d), the variables on the left hand side of each equation are the endogenous variables in the SVARX (and which have lagged terms as exogenous variables on right hand side) while the rest of the variables are exogenous ; ind_y represents industrial sector output; $\overrightarrow{elec\_avail}$ represents a vector of electricity availability components defined in the spirit of Rohan and Burke (2018) and which comprise of electricity installed capacity, electricity supply volatility used as a proxy for electricity supply quality, electricity consumption and electricity access rate; $ind\_tariffprice$ represents industrial electricity price; gkf represents gross fixed capital formation (gkf); ind_lbr represents industry labour; fdi represents foreign direct investment; ind_credit represents total commercial bank credit to the industrial sector; and u_t, ε_t, e_t & z_t are the error terms in the respective equations.

A practical method for testing causality relations is to regress each endogenous variable in (4a) - (4d) on its own lagged values and on lagged values of exogenous regressors and test the null hypothesis that the estimated coefficients on the lagged values of exogenous regressors are jointly zero. This is what the famous Wald Granger causality (Granger, 1969) test does. Thus, the SVARX models in (4a)-(4d) were estimated via the ordinary least squares procedure, and thereafter a Wald granger causality test (Granger, 1969) was employed to examine the direction of causality relationships in the model.

As for shock impact assessment, the impulse response functions (IRFs) are estimated and analyzed *after SVARX* estimation to establish the shock impacts in the independent variables on the dependent variable. Theoretically, an IRF measures the effect of a shock to an endogenous variable on itself or on another endogenous variable (L¨utkepohl, 2005; Becketti, 2020). In other words, IRFs describe how the innovations to one variable affect another variable after a given number of periods.

Extending the version of equation (2), we can write the p[th] order structural vector autoregressive model with exogenous variables (SVARX) as:

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B x_t + u_t \quad (5);$$

Where:
y_t is a K x 1 random vector, the A_i are fixed K x K matrices of parameters, x_t is an R_0 x 1 vector of exogenous variables, B is a K x R_0 matrix of coefficients, v is a K x 1 vector of fixed parameters, and u_t is assumed to be white noise process such that:

$$E(u_t) = 0; E(u_t u_t') = \Sigma\,;\ E(u_t u_s') = 0 \text{ for } t \neq s \quad (6)$$

The SVARX in equation (5) says that the endogenous variable y_t is a functions of its own lags, other exogenous variables (x_t) and serially uncorrelated innovations u_t. Assigning a causal interpretation to IRFs and FEVDs after SVARX estimation requires that the exogenous variables be strictly exogenous, that is, $E(x_{js} u_{it}) = 0$ for all, j, s and t .

To see how the shocks affect the variables in y_t after, say, i periods, we can rewrite the model in (5) in its moving-average form (assuming that the SVARX is stable) so that we have:

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i\, u_{t-i} \quad (7);$$

where: μ is the K x 1 time-invariant mean of y_t, and

$$\Phi_i = \begin{cases} I_K & If\ i = 0 \\ \sum_{j=1}^{i} \Phi_{i-j} A_j & If\ i = 1.2, \ldots \end{cases} \quad (8)$$

In equations (7) and (8); the Φ_i are the simple IRFs. The j, k element of Φ_i give the effect of a 1–time unit increase in the k^th^ element of u_t on the j^{th} element of y_t after i periods, holding everything else constant.

It is however important to note that the shock impacts in relation to equation (7) have no causal interpretations, but rather provide the direction of shock impacts and the length of time the impacts may last. The IRFs in relation to equation (7) provide no causal interpretations because of potential contemporaneous correlation among the u_t, which implies that a shock to one variable is likely to be accompanied by shocks to some of the other variables, so it does not make sense to shock one variable and hold everything else constant in this case. Nevertheless, this short coming has a solution: we can rewrite equation (7) in terms of mutually uncorrelated innovations (Sims, 1980).

Suppose that we had a matrix$P$, such that: $\Sigma = PP'$, then:

$$P^{-1}\,\Sigma\,P'^{-1} = I_K \quad (8);$$

and:

$$E[P^{-1}\,u_t\,(P^{-1}\,u_t)'] = P^{-1}E[(u_t u_t')P'^{-1}] = P^{-1}\Sigma P'^{-1} = I_K\, I_K \qquad (9)$$

We can thus use P^{-1} to orthogonalize the u_t and rewrite equation (18) as:

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i\, PP^{-1} u_{t-i} \qquad (10)$$

Now using equation (10) for IRF analysis will provide shock effects with causal interpretation without losing any information even if other factors are held constant.

4. Findings

4.1 Presentation of the descriptive statistics on the main study variables

We begin by presenting the descriptive statistics of interest on the main study variables. To facilitate actuality of meaning, the descriptive statistics of are generated on the variables in their original units of measurement. Table 1 gives the summary of the mean value, minimum value, maximum value and coefficient of variation for each variable.

Table 1

The mean, minimum, maximum value and coefficient of variation of the main study variables (variables are in their original units of measurement)

Variable Name	N	Mean	Min.	Max.	Std.Dev	CV
Industrial output, Value added, billion US $	60	8.9	6.1	12.9	1.8	0.20
Electricity installed capacity, total, MW	60	1061.9	629.5	2101.7	307.3	0.29
Electricity consumption, total, million kWh	60	663.5	317.0	1094.6	205.2	0.31
Electricity Access, percentage	60	29.0	9.5	47.7	13.8	0.48
Electricity supply volatility, 3-qtr MA std. Dev ('000, MWh)	60	38.2	2.1	378.7	57.6	1.5
Industrial electricity prices, Ug.Shs/kWh	60	364.8	268.4	449.0	46.9	0.13

Source: Author's compilation from analysis of raw data

Estimates of the coefficient of variation (CV): The coefficient of variation represents the percentage ratio of a variable's standard deviation to its mean. Among many applications and usefulness, the absolute values of CV can help to identify which variables show higher variability or dispersion compared to other variables, even when the relative means of the variables are substantially different (Bedeian & Mossholder, 2000). The variables with very high variability can present estimation challenges especially when they appear as dependent variables, because such variables are normally associated with deviation from normal distribution. In most applied research, a CV of less than 30 percent represents low variability in the data on a given variable, a CV that falls between 30 percent and 42 percent is an indicative of moderate variability whereas a CV in excess of 42 percent is considered high and it may be a pointer (though subject to test) to departure from normal distribution (Salmito et al, 2018). According to the descriptive statistics summarized in Table 1, it is observed that the variables of electricity supply volatility, electricity consumption and electricity access have CV estimates in excess of 30 percent, suggesting high variability in these variables. On the other hand, the variables of electricity installed capacity, industrial electricity prices and industrial output have CV estimates less than 30 percent, suggesting moderate variability in these variables.

Estimates of the mean, minimum and maximum values: According to the descriptive statistics summarized in Table 1, industrial output for Uganda recorded an average of $ 8.9 billion over the study period, with a minimum of $ 6.1 billion and a maximum of $ 12.9 billion. The descriptive statistics summarized in Table 1 indicate that the average electricity installed capacity for Uganda over the study period was recorded at 1061.9MW with a minimum of 629.5MW and a maximum of 2101.7MW. The descriptive statistics summarized in Table 1 indicate that the average electricity consumption for Uganda over the study period was 663.5kWh with a minimum electricity consumption of 317.0kWh and a maximum electricity consumption of 1094.6kWh. The descriptive statistics summarized in Table 1 further indicate that electricity access for Uganda recorded an average of 29 percent over the study period with a minimum of 9.5 percent and a maximum of 47.7 percent. The volatility in electricity supply recorded an average of 38.2 MWh over the study period, with a minimum of 2.1 MWh and a maximum of 378.7MWh. Last by not least, the descriptive statistics summarized in Table 1 show that the industrial electricity prices recorded an average of 364.8 Ug.Shs/kWh with a minimum of 268.4 Ug.Shs/kWh and a maximum of 449.0 Ug.Shs/kWh.

4.2 Unit root test results in the empirical model

The study employed the Augmented Dickey-Fuller (ADF) unit root testing procedure to test for presence of unit roots in all the variables in the empirical model, under the null hypothesis that the variable under investigation has a unit root, meaning that it is non-stationary. Lag order selection in the ADF tests has been chosen by the Akaike's information Criteria (AIC). The summary of unit root tests results, lag selection order and the order of integration (OOI) of the study variables are summarized in Table 2.

Table 2
Unit root test results on all variables in the empirical model

Variable	Levels Lags	Levels ADF Z(t) Stat.	Levels Prob. for Z(t)	First Differences Lags	First Differences ADF Z(t) Stat.	First Differences Prob. for Z(t)	OOI
Log of industrial sector output	2	0.34	0.9793	1	-4.18***	0.0007	I(1)
Log of electricity installed capacity	2	0.39	0.9810	3	-4.77***	0.0001	I(1)
Log of electricity supply volatility	1	-3.21**	0.0194	--	--	--	I(0)
Electricity access	2	-0.94	0.7745	3	-7.62***	0.0000	I(1)
Log of electricity consumption	2	-0.99	0.7537	3	-4.99***	0.0000	I(1)
Log of industrial electricity prices	3	-2.84*	0.0525	1	-6.33***	0.0000	I(1)
Log of gross fixed capital formation	2	-1.11	0.7128	4	-3.20**	0.0201	I(1)
Log of foreign direct investment	4	-0.57	0.8772	3	-4.89***	0.0000	I(1)
Lending rate	2	-1.89	0.3343	4	-3.15**	0.0230	I(1)
Industrial Labour	2	-2.92**	0.0415	--	--	--	I(0)

Source: Author's compilation. ***p<0.01; ** p<0.05; OOI =Order of Integration

The unit root test results summarized in Table 2 indicate that the estimated ADF z-statistics reject the null hypothesis of having a unit root at 5 percent level of significance for the logarithm of electricity supply volatility and for industrial labour variables in levels. This result suggests that the logarithm of electricity supply volatility and for industrial labour are integrated of order zero, I (0). On the other hand, estimated ADF z-statistics do not reject the null hypothesis of having a unit root at 5 percent level of significance for the logarithm of industrial sector output, the logarithm of electricity installed capacity, electricity access, the logarithm of electricity consumption, the logarithm of industrial electricity prices, the logarithm of gross fixed capital formation, the logarithm of foreign direct investment and lending interest rate in levels but the estimated ADF z-statistics reject the null hypothesis that each of the aforementioned variables has a unit root in its first difference at 5 percent level of significance. The unit root test results therefore indicated that whereas the logarithm of electricity supply volatility and industrial labour are I(0), the rest of the study variables are I(1).

4.3 Cointegration test results

The study employed the Johansen (1995) cointegration test procedure to test for presence of long run equilibrium relationship in the relationship being investigated. Even though the Johansen (1995) cointegration test has been said to be most appropriate cointegration method with I (1) variables, some scholars (e.g. Nkoro & Uko, 2016) argue that the Johansen (1995) cointegration test can still be used but may not be robust if there are less than two cointegrating vectors in the model. Kripfganz (2014) has suggested that cointegration in a model with a mix of I (1) and I (0) variables can only exist among I (1) variables in the model, though one can still have a long-run relationship among I (0) variables but not necessarily calling it cointegration (Kripfganz, 2014). Table 3 shows the summary of the cointegration test results from Johansen and Juselius (1990) cointegration test.

Table 3
The Johansen Cointegration test results in the empirical model

Max. rank (r)	Eigen Value	Trace statistic	Critical value at 5 percent
r≥0	-	740.7499	192.89
r≥1	0.97625	531.2993	156.00
r≥2	0.93826	375.3483	124.24
r≥3	0.90899	241.1266	94.15
r≥4	0.81092	197.2878	72.26
r≥5	0.78579	154.8432	68.52
r≥6	0.67134	92.5300	47.21
r≥7	0.55878	46.7104	29.68
r≥8	0.38016	19.9262	15.41
r≥9	0.29513	**0.3402***	3.76
r≥10	0.00606	--	--

Source: Compiled by the author from analysis of raw data

According to the Joahansen cointegration test results in Table 3, the trace statistic rejects the null hypothesis that there are no more than r = 9 (or H_o: r ≥ 9) cointegrating relations in empirical model. This is because at r ≥ 8, the critical value exceeds the Trace statistic value, which implies that the null hypothesis of r ≥ 9 is rejected at 5 percent level of significance. Such cointegration test results suggest that there are in fact ten (i.e. r = 10) cointegrating relations in in the relationship being investigated.

4.4 Assessment of the causality relations after SVARX estimation

The causality relations among the study variables of interest were assessed by implementing the granger causality Wald tests after estimating a Structural Vector Auto Regression with exogenous regressors (SVARX) model, in which the electricity availability dimensions (i.e. Logarithm of electricity installed capacity, logarithm of electricity supply volatility, logarithm of electricity consumption and electricity access), logarithm of industrial electricity prices and logarithm of gross fixed capital formation were treated as endogenous variables while logarithm of foreign direct investment, lending rate and industrial labour were treated as exogenous variables.

It should be noted that running the granger causality Wald tests are possible when the SVARX is exactly identified. Thus, to achieve an exactly identified model in a 6-endogenous variable SVARX model, we imposed exactly 15 restrictions on the parameters of the A and B equality constraint matrices which represent the contemporaneous relationships between the variables in the model. Lag selection in the underlying VAR has been determined by the Akaike's information criteria (AIC). The results from the granger causality Wald test results are summarized in Table 4.

Table 4
The Granger causality Wald test results after SVARX estimation (only the endogenous variables in the SVARX model are indicated)

Variable Equation	Excluded variable	Estimated Chi-sq. stat.	Prob > chi-sq.
Δ(Logarithm of industrial output)	Δ(logarithm of electricity installed capacity)	11.45**	0.022
	Δ(electricity access)	51.22***	0.000
	Δ(logarithm of electricity consumption)	15.48***	0.000
	logarithm of electricity supply volatility	43.58***	0.000
	Δ(logarithm of industrial electricity prices)	8.50*	0.075
	Δ(logarithm of gross fixed capital formation)	85.12***	0.000
	ALL	222.52***	0.000
Δ(logarithm of electricity installed capacity)	Δ(Logarithm of industrial output)	4.04	0.401
Δ(electricity access)	Δ(Logarithm of industrial output)	21.32***	0.000
Δ(logarithm of electricity consumption)	Δ(Logarithm of industrial output)	18.98***	0.000
logarithm of electricity supply volatility	Δ(Logarithm of industrial output)	0.40	0.983
Δ(logarithm of industrial electricity prices)	Δ(Logarithm of industrial output)	3.63	0.458
Δ(logarithm of gross fixed capital formation)	Δ(Logarithm of industrial output)	64.54***	0.000

Source: Author's compilation from analysis of raw data. *p>0.1; ** p>0.05; *** p>0.01

Beginning with the electricity availability components investigated in this study, the Granger causality Wald test results, as summarized in Table 4, indicate that the estimated chi-square statistics reject the null hypothesis that each of the four electricity availability indicators included in the SVARX model (i.e. logarithm of electricity installed capacity, logarithm of electricity consumption, electricity access and logarithm of electricity supply volatility) do not granger cause the logarithm of industrial sector output at 5 percent level of significance. The Granger causality Wald test results, as summarized in Table 4, also indicate that the estimated chi-square statistic rejects the null hypothesis that the logarithm of gross fixed capital formation does not granger cause the logarithm of industrial sector output at 5 percent level of significance. On the other hand, the Granger causality Wald test results, as summarized in Table 3, indicate that the estimated chi-square statistic does not reject the null hypothesis that logarithm of industrial sector prices does not granger cause the logarithm of industrial sector output at 5 percent level of significance.

Going forward, the estimated chi-square statistics from the Granger causality Wald test, as summarized in Table 4, reject the null hypothesis that the logarithm of industrial output does not granger cause the variables of electricity access, logarithm of electricity consumption and logarithm of gross fixed capital formation at 5 percent level of significance respectively. On the other hand, the estimated chi-square statistics from the Granger causality Wald test, as summarized in Table 4, do not reject the null hypothesis that the logarithm of industrial output does not granger cause the variables of logarithm of electricity installed capacity, logarithm of electricity supply volatility and logarithm of industrial electricity prices at 5 percent level of significance respectively.

In a nutshell, the granger causality test results reveal four key outcomes in relation to causality relationships between electricity availability, electricity prices and industrial sector output in Uganda: (1) there is a bidirectional causality between industrial sector output and electricity access, (2) there is a bidirectional causality between industrial sector output and electricity consumption, (3) there is a unidirectional causality running from electricity installed capacity to industrial sector output, (4) there is a unidirectional causality running from electricity supply volatility to industrial sector output, and (4) there is no causality between industrial electricity prices and industrial sector output.

4.4.1 Assessment of the shock effects in the final SVARX model for objective two

In addition to causality assessments among the study variables, the study assessed how the shocks in the industrial sector output stimulus variables impact industrial sector output growth for Uganda. This has been achieved by estimating and providing a causal interpretation of the simple impulse response functions (IRFs). In this endeavor, the study conducted the directional shock impact assessments, analyzed the extent of the shock and determined the length of the shock impact, while focusing on the analysis of the responses of industrial sector output to shocks in the electricity availability indicators under investigation and to shocks in the industrial electricity prices.

We present the IRF estimates in tabular form alongside the IRF grid graphs of the individual responses accruing from an implemented shock in each of the key predictors of the industrial sector output as indicated as follows:

Analysis of the impact of a shock to electricity installed capacity on industrial sector output growth

Figure 1

Irf: imp(logelectrinstcap) resp (logind_ouput)

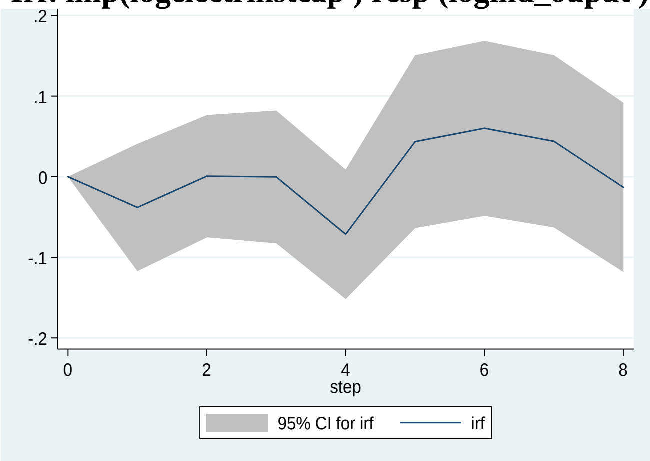

Table 5

Irf: imp(logelectrinstcap) resp (logind_ouput)

Qtr/ Step	IRF	Lower bound	Upper bound
2	0.000700	-0.075064	0.076465
3	-0.000225	-0.08249	0.082040
4	-0.071396	-0.151632	0.008841
5	0.043516	-0.063570	0.150603
6	0.060194	-0.048270	0.168657
7	0.043954	-0.062802	0.150709
8	-0.013097	-0.118049	0.091854
0	0	0	0
1	-0.038123	-0.117044	0.040798

Source: Generated by author from analysis of raw data

According to the IRF estimates summarized in Table 5 and represented graphically in Figure 1, it is observed that a shock to electricity installed capacity will have somewhat weak to moderate asymmetric positive and negative impacts on the industrial sector output within the first eight quarters (within 2 years) but the shock in the electricity installed capacity will leave industrial sector output with a negative impact in the 8th quarter. More specifically, the IRF estimates in Table 5 and Figure 1 indicate that a shock in the electricity installed capacity will have a negative impact on the industrial sector output within the first, third, fourth and eighth quarters time period, and will have a positive impact within the second, fifth, sixth and seventh quarters time period, the shock effect appears to persist after the eighth quarter.

Analysis of the impact of a shock to electricity access on industrial sector output growth

Figure 2

Irf: imp(electricity access) resp (logind_ouput)

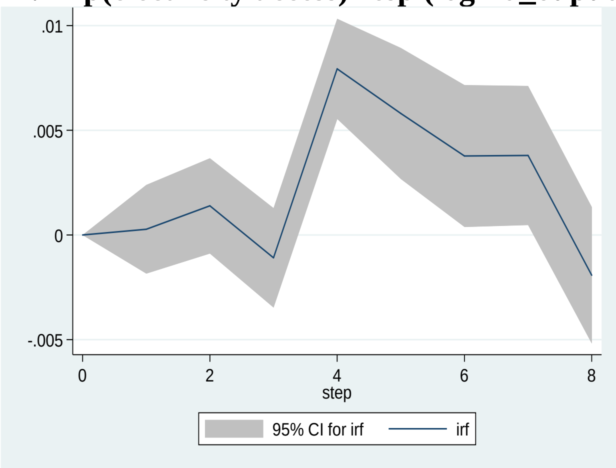

Table 6

Irf: imp(electricity access) resp (logind_ouput)

Qtr/ Step	IRF	Lower bound	Upper bound
0	0	0	0
1	0.000273	-0.001845	0.002390
2	0.001392	-0.000883	0.003666
3	-0.00109	-0.003463	0.001283
4	0.007935	0.005543	0.010327
5	0.005805	0.002675	0.008935
6	0.003773	.0000384	0.007162
7	0.003798	0.000478	0.007118
8	-0.001923	-0.005183	0.001336

Source: Generated by author from analysis of raw data

The IRF estimates with respect to a shock in electricity access, as indicated in Table 6 and represent in a grid graph in Figure 2, show that a shock to electricity access will have asymmetric positive and negative effects on industrial sector output, but with more of the positive asymmetric effects over the first eight quarters. Although the shock effects of electricity access appear to persist after the eight quarter time period, the IRF is confined within small area of the confidence band defined by a small range of the confidence limits. This suggests that a shock to the electricity access will have a small probability that it will in fact impact on the industrial sector output.

Analysis of the impact of a shock to electricity supply volatility on industrial sector output growth

Figure 3

Irf: imp(electricity supply vol) resp (logind_ouput)

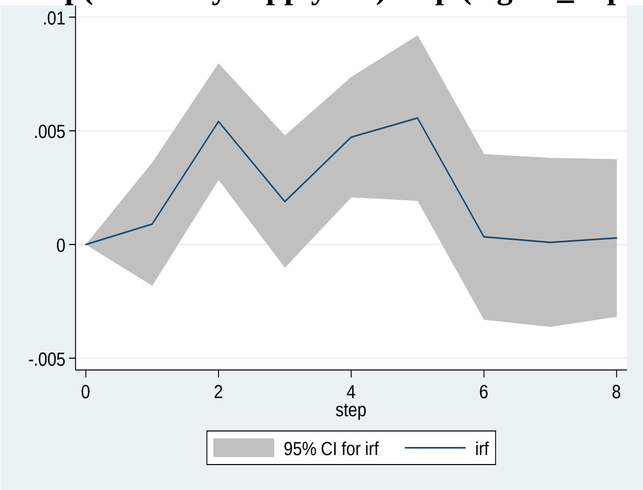

Table 7

Irf: imp(electricity suplly vol) resp (logind_ouput)

Qtr/ Step	IRF	Lower bound	Upper bound
0	0	0	0
1	0.000897	-0.001806	0.003600
2	0.005409	0.002852	0.007966
3	0.001888	-0.001016	0.004792
4	0.004722	0.002076	0.007367
5	0.005563	0.001929	0.009198
6	0.000338	-0.003303	0.003979
7	0.000094	-0.003617	0.003805
8	0.000288	-0.003173	0.003749

Source: Generated by author from analysis of raw data

As for the impact of a shock in the electricity supply volatility on industrial sector output growth, the estimates of the IRF as summarized in Table 7 and represented in a grid graph in Figure 3 indicate that industrial sector output responds positively but asymmetrically to a shock in electricity supply volatility over the first six quarters, thereafter the positive shock impact almost dies out. The IRF grid shows that the IRF is confined within a small range of values of the confidence limits, suggesting that there will be a small probability that the shock to the electricity supply volatility will impact on industrial sector output.

Analysis of the impact of a shock to electricity consumption on industrial sector output growth

Figure 4
Irf: imp(ind_electricity prices) resp (logind_ouput)

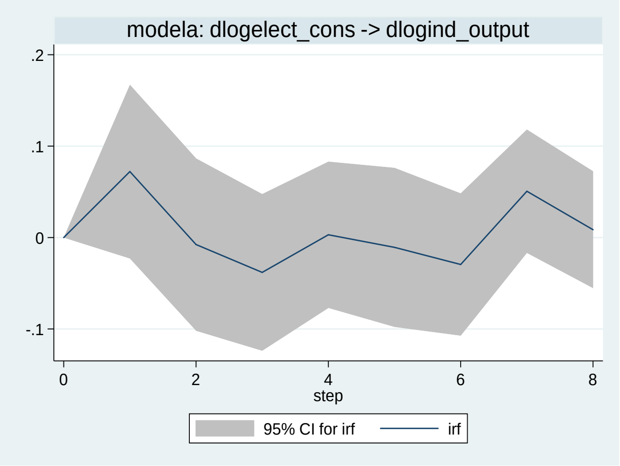

Table 8
Irf: imp(ind_electricity prices) resp (logind_ouput)

Qtr/ Step	IRF	Lower bound	Upper bound
0	0	0	0
1	0.072164	-0.022784	0.167111
2	-0.007645	-0.101829	0.086539
3	-0.038094	-0.123715	0.047528
4	0.003065	-0.076928	0.083058
5	-0.010718	-0.097685	0.07625
6	-0.029434	-0.107156	0.048287
7	0.050688	-0.016742	0.118118
8	0.008642	-0.055195	0.072479

Source: Generated by author from analysis of raw data

The IRF estimates with respect to a shock in electricity consumption, as indicated in Table 8 and represent in a grid graph in Figure 4, industrial sector output responds positively and negatively at different time periods to a shock in electricity consumption over the first eight quarters. However the shock effect to electricity consumption on industrials sector output appear to disappear rather quickly towards the eight quarter.

Analysis of the impact of a shock to industrial electricity prices on industrial sector output growth

Figure 5
Irf: imp(ind_electricity prices) resp (logind_ouput)

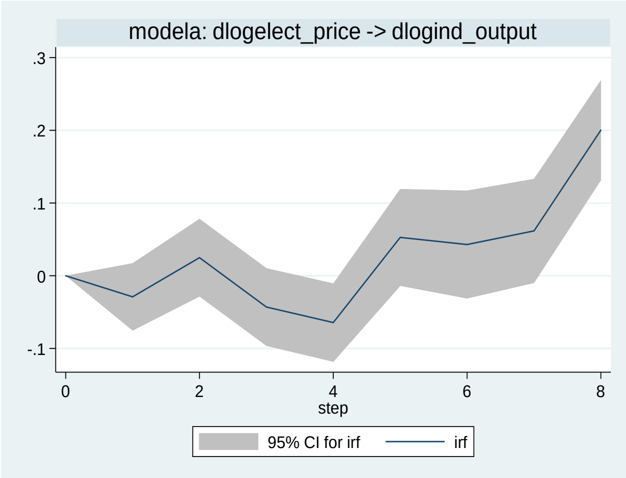

Table 9
Irf: imp(ind_electricity prices) resp (logind_ouput)

Qtr/ Step	IRF	Lower bound	Upper bound
0	0	0	0
1	-0.028991	-0.075273	0.017290
2	0.024848	-0.028538	0.078235
3	-0.042998	-0.096363	0.010366
4	-0.064366	-0.118213	-0.010519
5	0.052782	-0.01376	0.119324
6	0.042932	-0.031234	0.117098
7	0.061682	-0.009924	0.133287
8	0.200248	0.131525	0.268972

Source: Generated by author from analysis of raw data

The results of IRF estimates indicated in Table 9 with a grid graph in Figure 5 indicate that a shock to the industrial electricity prices has positive and negative asymmetric effects on the industrial sector output over the first four quarter period, thereafter, the shock in the electricity prices has positive asymmetric effects on the industrial sector output. The findings indicate that the shock effects of industrials electricity prices persist even after the first eight quarters of the year.

5.0 Concussion and policy implications

The study sought to investigate the causality relationships and assess shock effects between electricity availability, electricity prices and industrial sector performance in Uganda. The study used quarterly time series data for the period 2009-2024in the investigation. Causality relationships were investigated employing the Wald granger causality tests conducted after estimating a Structural Vector Auto Regression with exogenous regressors (SVARX). Shock impact assessment was achieved by estimating and assessing the impulse response functions (IRFs) after SVARX estimation. Findings from causality test reveal that (i) there is a bidirectional causality between industrial sector output and electricity access, (ii) there is a bidirectional causality between industrial sector output and electricity consumption, (iii) there is a unidirectional causality running from electricity installed capacity to industrial sector output, (iv) there is a unidirectional causality running from electricity supply volatility to industrial sector output, and (v) there is no causality between industrial electricity prices and industrial sector output. Findings further indicate that a shock to the variables of electricity installed capacity, electricity access and industrial electricity prices will have asymmetric positive and negative impact on industrial sector output which appear to persist even after the first eight quarters time period. On the other hand, findings from shock impact analysis indicate that a shock to electricity supply volatility and a shock to electricity consumption will have asymmetric effects on the industrial sector output but which appear to die out in the eight quarter. However, the asymmetric effects on the industrial sector output caused by shocks in the electricity installed capacity, electricity access and industrial electricity prices appear to persist even after the eight-quarter time period.

In terms of policy direction, findings from this study suggest that deliberate policies should be directed toward cushioning the electricity installed capacity, electricity access and industrial electricity prices to both external and internal shocks for realization of sustainable industrial sector output growth in Uganda.

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