Studies of African Economies vol.5

From Past to Future

Mangalani P. Makananisa
Benjamin Yamb
Editors

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Mangalani P. Makananisa

South African Revenue Service, South Africa

Benjamin Yamb

University of Douala, Cameroon

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Studies of African Economies: From Past to Future, Vol.5

Editors: Mangalani P. Makananisa [a] & Benjamin Yamb [b]

[a] South African Revenue Service, South Africa.

[b] University of Douala, Cameroon.

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Preface

(Ch.1) The objective of this paper is to determine the gender wage gap in the informal sector in Togo. To do so, the method of decomposition of the refocused influence function (RIF) was applied to data from the integrated regional survey on employment and the informal sector (ERI-ESI) in WAEMU member states carried out by the National Institute of Statistics and Economic and Demographic Studies (INSEED) in Togo (2019). The results reveal that men are better paid than women throughout the wage distribution. This gender wage gap is mainly due to differences in performance associated with productive characteristics. In addition, discrimination against women has increased in the low and medium quantiles, i.e. it has affected the poorest disproportionately. These results imply that in order to effectively combat the wage gap in the informal market in Togo, emphasis must be placed on those factors that explain the wage difference, namely education, experience and sector of activity.

(Ch.2) The paper seeks to examine the way subsistence housing has become a challenge to Dar es Salaam city's competitiveness. A literature review and conducting interviews were the methods used to collect data. Findings indicate that there is large quantity of subsistence housing in Dar es Salaam. The situation has reduced the high degree of urban competitiveness in a number of ways, which include increased productivity, improvement of the life of its citizens, as well as providing higher quality of social services. The paper argues for the improvement of subsistence housing by involving central and local governments, private sector, civil society organizations, the community and the international organizations to work in partnershipin order to increase the city's competitiveness.

(Ch.3) Over estimation and under estimation of the Personal Income Tax (PIT) revenue results in an unstable economy and unreliable statistics in the public domain. This study aimsto find a suitable SARIMA and Holt–Winters model that suits the sample monthly data for PIT well enough, from which a forecast can be generated. This study uses the aspects of time series model (Holt–Winters and SARIMA) and regression models with SARIMA errors to simulate the structure which followed the historical actual realization of PIT. The quarterly data were obtained from quarter1, 2009 to quarter 1, 2017 for the purpose of modeling and forecasting. The data were divided into training (quarter 1, 1995 to quarter 1, 2014) and testing (quarter 2, 2014 to quarter 1, 2017) data sets. The forecast from quarter 2, 2017 to quarter 1, 2020 were also derived and aggregated to annual forecast. Holt–Winters, SARIMA and Time Series Regression models fitted captured the movement of the historical PIT data with higher precession. The generated forecast is recommended to avoid several model revisions when locating the actual PIT realisation. However, monitoring of this model is crucial as the prediction power deteriorate in a long run. The study recommends the use of these methods for forecasting future PIT payments because they are precise and unbiased when forecasting are made. This will assist the South African authorities in decision making for future PIT revenue.

(Ch.4) The unprecedented demographic growth coupled with high rates of unemployment has led to the increased rate of farming activities on the Western slopes of the Manengouba Mountain. The shift from local livestock rearing and shifting cultivation of Cocoyams production to intensivo- extensive cropping of tomatoes, Irish potatoes, lettuce, huckleberry, cabbages and carrots, shows spatial signatures on space colonization in the Eboga caldera of the Manengouba Mountain and its environs. This hypothesis was tested through a multi- disciplinary and systematic approach; wherein, primary and secondary data were collected on the field later treated. This article brings out the trends or traits around this mountain, propose ways in which sustainable farming practices can be carried out so as to reduce soil erosion and pollution as well as methods to increase productivity so as to supply areas within and beyond the confines of the production basin.

(Ch.5) This chapter estimates the size and development of the South African shadow economy (SE) using two indirect approaches namely, the Multivariate Indicator Multivariate Causes (MIMIC) model and the Currency Demand Approach (CDA). The study uses time series from 2000 to 2019 (using quarterly data) to estimate the SE of South Africa for the period 2004 to 2018. The average estimated size of the SE from the CDA and MIMIC model are 22.47% and 25.45% respectively. Overall, the MIMIC and CDA models are both showing a slight decreasing trend for the same period. The study recommends further analysis to be conducted on economic segments in order to explore the SE activity distribution between different economic sectors; resulting in an easier way to identify, locate and monitor unrecorded businesses and also increase revenue collections and minimise non-compliance for different sectors.

(Ch.6) The performance and the efficiency of a business are related to the decision-making process, which requires a considerable amount of up-to-date, relevant and high-quality data, information and knowledge. In this context, learning is considered to be a process of acquiring knowledge, and can be simulated using artificial neural networks. The application of artificial intelligence in the decision-making process within a company enables decision-makers to analyze and process knowledge and data external or internal to the company in order to make a better decision considered optimal. This paper uses a model based on the multilayer perceptron neuron network to predict the nature of the decision. A batch learning algorithm is used as a tool for the selection of the most relevant factors in the decision-making process. The results demonstrate the relevance of the neural approach with an offline algorithm in this area of research. On a sample of 200 decision-makers, the model predicted the nature of the decision with a correct classification rate equal to 84.2%. This model enabled us to determine the optimal combination of factors that help to reach a good predictive performance of the nature of decision.

Editors
M.P. Makananisa & B. Yamb
May 20, 2020

Notes on Contributors

Koami Mawuko **Midagbodji:** PhD in Development Economics at the University of Lomé in Togo. His research focuses on the issues of youth employment and employability, poverty, inequality and health. He also works on issues of entrepreneurship in different segments of the labour market. Currently, he is a consultant on the different projects developed for young Togolese people, namely the National Project for the Promotion of Rural Entrepreneurship (PNPER) funded by IFAD, the Employment of Vulnerable Youth (EJV) project funded by the World Bank. It should be noted that he is a certified GERME trainer at the International Labour Office (ILO). He has also led several training sessions in entrepreneurship on the creation and management of businesses and on coaching business idea bearers in the drafting of business plans.

Dédé **Kouevidjin:** Doctoral student in Development Economics at the University of Lomé in Togo. Her research focuses on issues of income distribution, poverty and inequality, private and public investment. She has also worked on social security issues in the informal sector as well as on agricultural productivity and poverty reduction with funding from the Partnership for Economic Policy (PEP) through the Community-Based Monitoring System (CBMS).

Komi **Agbeti:** Economic Statistics Engineer (ISE), is currently Head of Division of Socio-demographic and Household Living Conditions Studies at the National Institute of Statistics and Demographic Studies (INSEED) in Togo. Apart from designing and conducting surveys on household living conditions, his studies focus on child labour, employment and employability of young people in sectors that are conducive to employment, in-depth analysis of poverty, multidimensional poverty, the demographic dividend, and the perception and cost of corruption. It is also responsible for the design and production of indicators for the domestication and monitoring-evaluation of the results framework of indicators of international agendas such as the Sustainable Development Goals (SDGs), Agenda 2063 and the National Development Plan (NDP).

Juma **Kiduanga:** Juma Kiduanga is a Senior Lecturer at the Institute of Development Studies. He holds Ph.D. in Development Studies from the University of Dar es Salaam. As a scholar he conducted many researches on the field of Urban Housing and published a number of articles focusing on housing in international and local journals. He is co-author of the book titled Urban Poverty as Inequalities and Capability Deprivations in Africa. The Case of Dar es Salaam. He implemented a number of research projects. Among the research projects implemented include Land Management, Urban Governance and Leadership: The Future of Urban Tanzania (UrbTan) funded by Danida, The Impact of Structural Adjustment Programmes on Rental Housing in Dar es Salaam and Mbeya Cities funded by OSSREA, Community Disaster Management Capacity in Informal Settlements of Mwanza City, Tanzania funded by SIDA/SAREC. From 2017 to 2019 he was coordinating the UDSM Core Team for the African Research Universities Alliance (ARUA) collaborative research group in Urbanization and Habitable Cities. As a member of Tanzania Urbanization Laboratory (TULab) he is involved in providing expertise in the field of urbanization to the two institutions coordinating TULab in Tanzania namely, the Ministry of Finance and Planning and Economic and Social Research Foundation. As a member of academic staff of IDS he teaches Political Economy, Rural-Urban Development and Poverty Reduction Strategies courses.

Mangalani Peter **Makanisa:** Mangalani Peter Makananisa was born and grew up in Magau village in Limpopo, South Africa on May 01, 1980. His home language is Tshivenda with English as the second language, a commonly used language in South Africa for communication. He is currently based in Pretoria. He holds anMSc degree inStatistics from the University of South Africa (UNISA) with an intention to further his studies along the same path and return to academia to share knowledge accumulated. Mangalani is more interested in statistics, data analytics, modelling, forecasting, computing and the use of artificial intelligent to solve real life problems. From July 2005, he has been employed by the South African Revenue Service (SARS) and has moved from various divisions within the organisation. Recently, he has been working for the Operational Research Unit (ORU) as a Specialist: Statistical Support.

Jean Luc **Erero:** Jean Luc Erero holds a Msc (Statistics), Mcom (Economics) and a Ph.D in Economics. Statistician-Economist with 15 years+ experience gained in government and non-government organisations. Demonstrated skills in static and dynamic computable general equilibrium (CGE) modeling and statistical analysis using GemPack software, GAMS and SAS. He is married with 4 children. Currently Jean Luc is working at the South African Revenue Service (SARS) as Specialist in Revenue Research and Analysis.

Nkumbesone Makoley **Essone:** Nkumbesone makoley Essone, holds a Ph.D in Geography from the University of Douala. He is Senior Lecturer of Geography, Geography Department, FALSH, University of Douala. He is currently, the coordinator of Professional Bachelor's degree programme in Environment and Sustainable Development. His research interest is in Metropolisation, Suburbanization, urban planning and Development and related problems, Urban- Rural Dynamics.

He is also an Assistant Chief Examiner, and Superintendent with the Cameroon GCE Board.

Etamesone **Diabe:** Assistant lecturer in the department of Geography university of Maroua holds a Ph.D in Environmental Geography from the University of Dschang. He has been an instructor, a member of Jury for Examinations, a member of the committee in charge of students' affairs in the Department of Geography of the same University. Dr. Sone is also a seasoned Advanced Level Geography Examiner at the Cameroon General Certificate of Education Examinations (GCE). He currently lectures in the Faculty of Arts, Letters and Social Sciences at the University of Maroua. His research interest on: Environmental protection and conservation, Natural and catalyzed hazards, Territorial Planning and Rural Development as well as Minority Groups and Tourism.

Ejuande Emmanuel **Wonomu:** Emmanuel Wonomu Ejuande is a Cameroonian, Ph.D student (Univ. of Douala). He holds a Master degree and a Bachelor degree in Geography (Univ. of Douala). Member of project team (SYSTALDO) and editorial board member of many publications; he has over five papers published at the national and international levels. He is equally a member of many scientific research groups and laboratories.

Mouna **Bekri:** Bekri Mouna is a PHD student researcher in economic sciences under the direction of Professor Ahmed Hachicha, economist, director of Studies, vice-Director of the ESC of Sfax. She is a member of the LRED laboratory. She is a secondary school teacher. Her research concerns economic intelligence, knowledge management, decision making processes and the integration of computer science and new technologies (python, deep learning, neural network, baysian network, robotics...) in these processes.

Ahmed **Hachicha:** is a Professor of Economics, a director of studies and vice director at High School of Business of Sfax, and a Research Associate in Laboratory of Economic Development at the Faculty of Economics and Management of Sfax (Tunisia). His research interests include the monetary economics, labor market, economic intelligence, regulation and institutions, economic freedom, subjective well being and econometric methods for program and monetary strategic policy evaluation. Professor Hachicha has supervised several PhD students and has written many papers and chapters in books published in good different ranked journals like Review of Quantitative Finance and Accounting, Handbook of Financial Econometrics and Statistics, Turkish of Economic Review, Applied Mathematics, Review of Pacific Basin Financial Markets and Policies, Asian Economic and Financial Review to name a few.

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1 Wage gap in the informal sector in Togo: A gender approach

Koami Mawuko **Midagbodji** [a †]
Dédé **Kouevidjin** [b]
Komi **Agbeti** [c]

Introduction

The labour market is very often characterized by gender disparities that can be explained by the characteristics of the workers and the firms that employ them (Gallen *et al.*, 2019). These inequalities are most evident in the highly disparate wage practices between men and women. The gender pay gap in the labour market has been the subject of in-depth studies for several decades, but remains an active and innovative area of research (Blau & Kahn, 2017). Economic theory teaches us that there are two main causes of discrimination. The "taste discrimination", which

[†] Laboratoire d'Economie Agricole et de la Macroéconomie Appliquée (LEAMA), Université de Lomé, 01 BP 1515, Lomé, Togo.
☎. +22890113949 ✉. enriquemida@yahoo.fr
[b] Laboratoire d'Economie Agricole et de la Macroéconomie Appliquée (LEAMA), Université de Lomé, 01 BP 1515, Lomé, Togo.
☎. +22890113949 ✉. kouevidjin54@gmail.com
[c] Institut National de la Statistique et des Etudes Economiques et Démographiques, INSEED, Togo.
☎. +22890113949 ✉. emmanuelfrancis@yahoo.fr

Becker (1957) was the first to model, refers to a situation where economic agents show a preference for certain groups while seeking to avoid interactions with others. Despite its cost, such discrimination may persist in competitive markets because some employers are willing to pay to avoid dealing with certain groups. Another form of discrimination that results from imperfect information about workers' abilities is called statistical discrimination. According to this analysis, introduced by Arrow (1973) and Phelps (1972), the employer assumes a correlation between gender or ethnic origin and the productivity of workers, hence certain differences in treatment. In this theoretical framework, the decomposition of wage differentials according to gender makes it possible to verify the existence of possible wage discrimination against a given gender group.

Many authors have studied gender inequalities in the labour market, looking at whether they are rather the result of differences in observable factors, such as elements of human capital (Olson, 2013), and the extent to which they remain unexplained after the influence of these characteristics has been neutralized. The unexplained part is generally equated with the effect of discrimination, although it actually covers other components. Some researchers suggest that wage inequality is due to discrimination against women in the labour market (Ahmed & Maitra, 2010), while others link the gender wage gap to the level of female human capital that is significantly lower than that of men (Hossain & Tisdell 2005). Education is one of the determining factors that cause gender wage differences in different regions (Pereira & Galego, 2013). Wage inequality increases with education in the informal sector (Atangana, 2019). To explain the components of the gender wage gap in Cameroon, Baye *et al*. (2016) found that a large part of the wage gap stems from differences in characteristics between men and women. According to Kimmel (1997) study on gender and racial wage differentials in rural areas, a larger part of the wage gap faced by women remains unexplained by employment and personal characteristics, implying that wage differentials for women are more due to differences in performance, while wage differentials for men are more due to differences in characteristics.

Developing countries have, on average, a higher proportion of informal employment than developed countries. In Togo, the informal sector accounts for 84percent of the labour force with an annual growth rate of 5percent and contributes between 28 and 40percent to GDP (AfDB, 2019). In terms of employment, 70 percent of female workers are confined to the informal sector (AfDB, 2019). In recent years, Togo has made progress on gender equality in legislative reforms. However, the country ranks 166th out of 188 countries on the gender inequality index in the 2016 Human Development Report. Indeed, gender discrimination and inequality still exist. Given the importance of the informal sector in job creation, an in-depth look at inequality in this sector deserves to be taken. Gender equality in employment is currently one of the greatest development challenges facing countries around the world, including those in Africa (Anyanwu & Augustine, 2013). Although much progress has been observed in recent decades around the world in terms of women's rights, it is clear that women have continued to be victims of many inequalities. Therefore, using data from the Employment and Informal Sector Survey, an analysis of gender differences in the Togolese informal labour market should provide new ingredients to shed light on the way forward in this direction. In this context, the study makes a number of empirical contributions so the main question is whether there is a gender wage gap in the informal sector in Togo? On this, two key questions emerge: (i) what is the extent of the gender wage gap in the informal sector in Togo? (ii) does the level of education play an important role in explaining the gender income gaps in the informal labour market in Togo? The answer to this question will allow us to say whether or not there is a gender wage gap.

The general objective is to determine the gender wage gap in the informal sector in Togo. Specifically, the aim is to: i) assess the gender wage gap in the informal sector in Togo; ii) determine the role of education in explaining the gender income gap in the informal labour market in Togo. No research work to our knowledge in Togo has examined gender wage differences in the labour market in general and the informal labour market in particular. Indeed, whether gender inequality exists in the informal sector in Togo remains an empirical question. Work on gender differences in Sub-Saharan Africa in general has focused mainly on the labour market as a whole, and few have addressed gender differences in the informal sector. In addition, this research draws on recently developed analytical tools. The unconditional quantile regression method RIF (Recentered Influence Functions) represents the improved version of the Oaxaca-Blinder decomposition method. The linearity of RIF regressions has several advantages. It is easy to reverse the proportions of interest by dividing by density. Since the inversion can be done locally, another advantage is that we do not need to evaluate the global impact at any point in the distribution and worry about monotony. The result is a simple regression that is easy to interpret.

The remainder of this article is organized in four sections. The first section focuses on the labour market in the literature. The second section presents the methodological approach, while the third section focuses on results and discussion. The conclusion and policy outlook are presented in the fourth section.

Literature review

Discrimination in the labour market is a situation in which people who provide labour market services and who are also physically or materially productive are treated unequally, which is related to an observable characteristic such as race, ethnicity or gender. This section is first devoted to the theory of discrimination, which remains the central theory of our research on labour market inequality. In order to understand the determinants of the wage gap in the labour market, we will review some empirical work on the wage gap in different segments of the labour market. While most of this work focuses on the role of education, some studies incorporate other socio-demographic factors.

The theory of labour market discrimination

The literature suggests two basic mechanisms: taste discrimination (Becker, 1957) and statistical discrimination (Arrow, 1973). This theory inspired by Becker (1971) is another way of introducing an effect of the social and family environment on the data and results of individual economic calculations. Some models of discrimination in the labour market can be distinguished. The first model views discrimination in terms of non-monetary motivations and nonprofit-maximizing behaviour (Becker, 1957). Becker (1957) states that his theory applies to discrimination and nepotism in all their manifestations. The second model is the one that either places the origin of discrimination outside the labour market (in the family or at school) or sees discrimination as behaviour aimed at minimizing costs. In contrast to Becker, Wood proposes a theory of the impact of workers' ideas about wage inequality justice on wage determination. For him, there are "normative" and "anomic" pressures that act on employers and employees: normative pressures include standards of fairness in wage gaps, while anomic pressures include those of competition and other market pressures. Statistical discrimination theory postulates that differential treatment of minority groups is motivated by imperfect information (Arrow, 1973). This model derives from the work of Arrow (1973) and Phelps (1972). Statistical discrimination models are the predominant alternative to taste-based models in the economic literature. In a class of statistical discrimination models, employers use observable race to substitute for unobservable skills (Phelps, 1972; Arrow, 1973).

Since the early work of Mincer (1958; 1974), Schultz (1961), Becker (1975), associated with human capital theory to explain gender wage differences in the labour market due to conflicting stocks of human capital, the literature on gender wage differences has continued to feed into the labour market, so that the concept has been extended to different areas of gender disparities, such as labour force participation and employment in the informal sector, among others. In economic theory, various explanations are proposed to justify differences in pay between groups or individuals. Under the assumption of perfect competition, gap-compensation theory teaches that differences in the difficulty of the tasks and skills of labour suppliers should lead to wage heterogeneity. While task difficulty differences are explained by Rosen (1974) formalized hedonic wage theory, skill-based wage differences are explained by Becker (1964) human capital theory. If it were possible to identify in the literature what, on the basis of this conceptual framework, explains the differences in wages between men and women by differences in human capital, it would be recognized that taking account of these differences in characteristics leaves a substantial part of the gender wage gap unexplained.

Empirical review

Gender wage discrimination and the size of the gender pay gap are frequent areas of research in labour economics. Empirical work on the gender pay gap largely confirms the existence of gender discrimination against women employees in the labour market. The calculation of discrimination shares and human capital endowment shares to explain wage differences between genders or races has been popularized by the wage decomposition methodology proposed by Blinder (1973) and Oaxaca (1973). Gallen *et al.* (2019) document the narrowing of the gap between the average wages of women and men in Denmark. They show that the decrease in the wage gap is due to the increase in the labour force, labour force participation and the increase in the number of hours worked by women, and to a lesser extent to a decrease in the gender wage gap. Ndamsa *et al.* (2015) used the ordinary least squares technique and the Oaxaca-Ransom decomposition to examine the role of male advantage and female disadvantage in assessing the discriminatory effect of the gender pay gap in the Cameroonian labour market and found that the discrimination component has an aggravating effect on the gender pay gap relative to the weak role of the staffing effect. Baye *et al.* (2016) used the Oaxaca-Blinder decomposition technique and an extension of the Oaxaca & Ransom (1994) decomposition to explain the components of the gender wage gap in Cameroon and found that a large part of the wage gap was due to differences in characteristics between men and women. However, they show that education, hours worked, agricultural employment and urban residence contribute in that order to a widening of the gender wage gap in terms of endowments, male advantage and female disadvantage.

Pereira & Galego (2013) studied wage differentials in Portugal. They found that education is one of the determining factors that cause gender wage differences in different regions. In addition to the level of education, they also found that the wage differential is generated by differences in work experience. Therefore, the wage differential is due to the difference in the years of work experience of each worker. More work experience can potentially lead to higher earnings. In terms of work experience, women are likely to have fewer years of work experience than men. Atangana-Ondoa (2019) analyses the effects of education on wage inequality in the informal sector in Cameroon using quantitative regression. He shows that wage inequality increases with education in the informal sector and that higher education creates the greatest inequality. Ariza & Montes-Rojas (2019) study recent inequality patterns and the effects of schooling on the distribution and informality of jobs on wage inequality in Argentina, Brazil, Colombia and Mexico. Using RIF regression unconditional quantile regression method and the random-coefficients quantile regression representation. The results show that the reduction in wage inequality is explained by the improvements in the lower part of the wage distribution in which the pricing rather than the composition effect explains most of the changes. Ingwersen & Thomsen (2019) decompose the wage gap using the unconditional quantitative regression model method RIF (regression of the refocused influence function) of the gross hourly wage on a set of explanatory variables. The results of the decomposition clearly indicate a significant increasing gap with higher wages for both foreigners (13.6 to 17.6 percent) and naturalized immigrants (10.0 to 16.4 percent). Furthermore, the results show a weak explanation for the wage gap in the low-wage deciles, which is even more pronounced among immigrant subgroups. Cultural and economic distances each have a significant influence on wages. However, a different appreciation of foreign credentials widens the wage gap considerably, by an average of 4.5 points.

Methodology

Model

The standard approach to analysing wage differences was first developed by Blinder (1973) and Oaxaca (1973). The objective of the method is to decompose differences in average wages between two groups. The wage-setting model is assumed to be linear and separable into observable and unobservable characteristics. Based on the Blinder-Oaxaca (1973) decomposition, several techniques have been proposed over the past decade to extend this approach to any point in the distribution. Although these new techniques are useful for decomposing wage differences across the distribution into a part explained by production characteristics and a part due to differences in output, most of them do not identify the contribution of each independent variable to the wage difference. The technique proposed by Fortin *et al*. (2011) overcomes this limitation by allowing the decomposition of differential wages in the Blinder-Oaxaca for any distribution statistic, so that it allows the contribution of each independent variable to the explained and unexplained evolution of the parts of the wage decomposition along the income distribution to be estimated.

A RIF-regression (Firpo *et al*., 2009; 2018) is similar to a standard regression, except that thedependent variable, $\boldsymbol{Y}$,is replaced by the (recentered) influence function of the statistic ofinterest. Consider IF $(y\,;v)$, the influence function corresponding to an observed wage $y$for the distributional statistic of interest, $v(F_Y)$. The recentered influence function (RIF) is defined asRIF$(y\,;\,v) = v(FY) + \mathrm{IF}(y\,;\,v)$, so that it aggregates back to the statistics ofinterest$\int RIF(y;\,v)\cdot dF(y) = v(FY) + \mathrm{IF}(y\,;\,v)$. In its simplest form, the approach assumes thatthe conditional expectation of theRIF $(\boldsymbol{Y}\,;v)$ can be modeled as a linear function of theexplanatory variables,

$$\mathbb{E}\left[\mathrm{RIF}\,(\boldsymbol{Y}\,;\,v)\,|X\right] = X\gamma \tag{1}$$

where the parametersγcan be estimated by OLS.

In the case of quantiles, the influence function $IF(Y, Q_\tau)$ is given by$(\tau - \mathbb{1}\{Y \leq Q_\tau\})/f_Y\,(Q_\tau)$, where $\mathbb{1}\{\cdot\}$ is an indicator function, $f_Y\,(\cdot)$, is the density of the marginal distribution of $\boldsymbol{Y}$, and Q_τ is the population τ-quantile of the unconditional distribution de $\boldsymbol{Y}$. As a result, RIF $(\boldsymbol{Y}\,;\,Q_\tau)$ is equal to $Q_\tau + IF(Y, Q_\tau)$, and can be rewritten as:

$$\text{RIF}\left(\boldsymbol{y}\,;\,Q_\tau\right) = Q_\tau + \frac{\tau - \mathbb{1}\{Y \le Q_\tau\}}{f_Y\,(Q_\tau)} = c_{1,\tau} \cdot \mathbb{1}\{Y > Q_\tau\} + c_{2,\tau} \tag{2}$$

where $c_{1,\tau} = \frac{1}{f_Y}(Q_\tau)$ and $c_{2,\tau} = Q_\tau - c_{1,\tau} \cdot (1-\tau)$. Except for the constants $c_{1,\tau}$; and $c_{2,\tau}$, the RIF for a quantile is simply an indicator variable $\mathbb{1}\{Y \le Q_\tau\}$ for whetherthe outcome variable is smaller or equal to the quantile Q_τ. Using the terminology introducedabove, running a linear regression of $\mathbb{1}\{Y \le Q_\tau\}$ on X is a distributional regression estimated a t$y = Q_\tau$, using the link function of the linear probability model. $(\Lambda(z) = z)$.

In the case of quantiles, the RIF is first estimated bycomputing the sample quantile $\widehat{Q_\tau}$ and estimating the density at that point using kernel methods. An estimate of the RIF of each observation, $\widehat{\text{RIF}}(Y\,;\,Q_\tau)$, s then obtained byplugging the estimates $\widehat{Q_\tau}$ and $\hat{f}(\widehat{Q_\tau})$ intoequation (2).

Letting the coefficients of the unconditional quantile regressions for each group be:

$$\hat{\gamma}_{g,\tau} = \left(\textstyle\sum_{i\in G} X_i \cdot X_i^T\right)^{-1} \cdot \textstyle\sum_{i\in G} \widehat{\text{RIF}}\left(Y_{gi};\, Q_{g,\tau}\right) \cdot X_i, \qquad g = A\,, B \tag{3}$$

we can write the equivalent of the OB decomposition for any unconditional quantile as :

$$\hat{\Delta}_o^\tau = \bar{X}_B\left(\hat{\gamma}_{B,\tau} - \hat{\gamma}_{A,\tau}\right) + (\bar{X}_B - \bar{X}_A)\hat{\gamma}_{A,\tau} \tag{4}$$

Where $\hat{\Delta}_o^\tau$ is the estimated wage gap between groups A and B on τ-quantile; $\bar{X}_A$; $\bar{X}_B$ are vectors of the average production characteristics for each group; $\hat{\gamma}_{A,\tau}$, $\hat{\gamma}_{B,\tau}$, are the estimated coefficients obtained by calculating the FIR on all variables in groups A and B on τ-quantile, respectively. The first term in equation (4) shows the portion of the wage gap that results from the different returns to productive characteristics of the two groups A and B, while the second term shows the portion of the wage differential that is due to differences in the endowments of productive characteristics between the groups. This equation makes it possible to identify the specific contribution of each of the groups considered variable to the estimated wage gap and of each of its components

Data

The data (in a snapshot) used in this research come from the Integrated Regional Survey on Employment and the Informal Sector (ERI-ESI) in WAEMU Member States. This survey was conducted by the National Institute of Statistics and Economic and Demographic Studies (INSEED) in Togo (2019). The general objective of the survey is to provide the baseline situation for monitoring employment and the informal sector in WAEMU member states. It includes a component on employment and another on the informal sector. The ERI-ESI survey covers 7200 households, including 2,600 in urban areas and 4,900 in rural areas, and includes 1,570 women and 5,930 men. The variables that are considered as control variables are those used in previous work mentioned in the literature review. In their recent work, authors such as Blau & Kahn (2017b) ; Gallen *et al.* (2019) have analysed the gender wage gap using a wide range of explanatory factors, including variables relating to human capital (education level), occupation (experience), industry (sector of activity). This allowed us to identify traditional variables related to the characteristics of individuals. Table 1 of the descriptive statistics gives the central trends of the variables retained in the empirical model.

Table 1. *Descriptive statistics*

Variables	Definition	Obs	Mean	Std.Dev.	Min	Max
LWAGE	Log du salaire	6522	10.903	1.248	6.908	16.118
EDUCATION	Education level	6522	.998	.904	0	3
EXPERIENCE	Experience	6522	3.011	1.268	1	5
AGE	Age	6522	1.535	.561	1	3
RESID	Place of residence	6522	.317	.465	0	1
SECTACT	Sector of activity	6521	2.322	1.214	1	4

Source: Authors, 2020.

Results and discussion

The RIF decomposition method proposed by Fortin *et al*. (2011) for gender wage gaps allows us to examine the total gap, the explained component and the unexplained component separately. Table 2 below presents the results of the decomposition of the gender wage gap in the informal sector. This table also shows the part of the gap that is due to different endowments of productive characteristics (explained part) and different returns to those characteristics (unexplained part). In other words, the figures in the *Explained* line give us the share of the gap that is attributed to differences in the values of the explanatory variables between men and women, while the figures in the *Unexplained* line give us the share due to differences in the estimated coefficients (the returns). Overall, the gender wage difference is clearly positive and significant at the 1% threshold for all quantiles and decreases monotonically along the quantiles, which confirms the results of Baye *et al*. (2016). Since women are taken as the benchmark, these positive values of the gender wage gap indicate that men earn higher wages than women. On average, the gender gap is about 1.081 log points. This confirms the existence of the wage gap in the informal sector. The wage gap is highest at the 10th percentile (1.274) while the 90th percentile has the lowest wage gap (0.754). In other words, discrimination against women has increased in the low and medium quantiles, i.e., it has affected the poorest very much. Furthermore, it is observed that the gender wage gap is mainly due to differences in performance associated with productive characteristics.

Thus the unexplained component of the gender pay gap is particularly pronounced across the distribution and is higher in the 10th quantile (which explains the total pay gap at 1.166% with a statistical significance of 1%). This shows that even if women have the same characteristics, they cannot always find jobs that pay as much as men. This corroborates the results of Bui & Imai (2019) where the wage gap between men and women was shared in approximately the same proportion between the two parties. For the detailed results of the component decompositions by individual characteristics, variables such as education, experience, and industry contribute significantly to the effects of the explained part of the gender wage gap. The positive and significant coefficients for educational attainment for the 10th, 25th, 50th, and 75th quantiles show that educational attainment leads to a larger wage gap for the poor than for the rich. This corroborates the findings of Atangana-Ondoa (2019) who finds that higher education creates more inequalities in the informal sector in Cameroon. As for the experience variable, the coefficients are significant and positive throughout the distribution. This reflects the fact that men are more experienced than women in the informal sector. This tendency is high in the first half of the distribution and low in the upper end. The same effects are observed for the sector of activity where its influence is high in the 25th and 50th quartiles of 0.111 and 0.102 respectively.

As for the unexplained part, the coefficients of the experience variable are significant and positive for the 25th and 50th quartiles but significant and negative for the upper quartiles. As a result, in the upper part of the distribution the most experienced women are less discriminated against than their less experienced counterparts in the informal sector. This implies that experience contributes to the increase in the wage gap in the first half of the distribution while it reduces the gap at the upper end of the distribution. Furthermore, for the place of residence, the results show that the wage gap between men and women is reduced in urban areas than in rural areas. This reflects the fact that women in urban areas are more experienced or better educated, which improves their performance and reduces the gender wage gap.

Table 2. *Results of the RIF decomposition of the gender wage gap*

VARIABLES	mean	q10	q25	q50	q75	q90	Gini
OVERALL							
MAN	11.22***	9.844***	10.48***	11.39***	12.18***	12.76***	0.0614***
	(0.0223)	(0.0200)	(0.0412)	(0.0244)	(0.0291)	(0.0327)	(0.000892)
WOMAN	10.14***	8.570***	9.630***	10.16***	11.34***	12.01***	0.0723***
	(0.0230)	(0.0392)	(0.0160)	(0.0157)	(0.0296)	(0.0357)	(0.00105)
DIFFERENCE	1.081***	1.274***	0.850***	1.234***	0.833***	0.754***	-0.0109***
	(0.0320)	(0.0440)	(0.0442)	(0.0290)	(0.0415)	(0.0484)	(0.00138)
EXPLAINED	0.207***	0.108***	0.329***	0.239***	0.190***	0.0650**	-0.00357***
	(0.0215)	(0.0199)	(0.0398)	(0.0242)	(0.0279)	(0.0297)	(0.000763)
UNEXPLAINED	0.874***	1.166***	0.521***	0.995***	0.643***	0.689***	-0.00735***
	(0.0352)	(0.0498)	(0.0617)	(0.0347)	(0.0426)	(0.0525)	(0.00160)
EXPLAINED							
EDUCATION	0.0498***	0.0267**	0.110***	0.0622***	0.0297	-0.0410*	-0.00154***
	(0.0145)	(0.0136)	(0.0278)	(0.0162)	(0.0197)	(0.0231)	(0.000568)
EXPERIENCE	0.0633***	0.0322***	0.0977***	0.0731***	0.0560***	0.0287***	-0.00106***
	(0.00932)	(0.00775)	(0.0167)	(0.0104)	(0.0108)	(0.0105)	(0.000320)
AGE	0.00571*	0.00258	0.00976*	0.00233	0.00557	0.00879**	-2.49e-05
	(0.00299)	(0.00263)	(0.00561)	(0.00308)	(0.00382)	(0.00448)	(0.000116)
RESID	-5.76e-05	0.000455	0.000545	4.01e-05	-0.000513	-0.000259	-1.62e-05
	(0.000380)	(0.00291)	(0.00349)	(0.000278)	(0.00328)	(0.00166)	(0.000104)
SECTACT	0.0879***	0.0463***	0.111***	0.102***	0.0996***	0.0687***	-0.000927***
	(0.0103)	(0.00871)	(0.0173)	(0.0118)	(0.0119)	(0.0103)	(0.000323)
INEXPLAINED							
EDUCATION	0.0224	-0.0196	0.126***	0.0604**	0.0152	-0.0402	-0.00211

	(0.0296)	(0.0417)	(0.0394)	(0.0262)	(0.0383)	(0.0458)	(0.00131)
EXPERIENCE	-0.0166	-0.0937	0.637***	0.390***	-0.213**	-0.415***	-0.0113***
	(0.0852)	(0.127)	(0.124)	(0.0783)	(0.108)	(0.124)	(0.00392)
AGE	0.149	0.0508	0.162	0.00874	0.219*	0.307**	-0.00141
	(0.0923)	(0.136)	(0.130)	(0.0849)	(0.119)	(0.141)	(0.00429)
RESID	-0.0886***	-0.111***	-0.0172	-0.0988***	-0.123***	-0.0339	0.00147
	(0.0228)	(0.0347)	(0.0368)	(0.0222)	(0.0265)	(0.0284)	(0.00111)
SECTACT	0.209***	0.354***	-0.366***	-0.310***	0.439***	0.579***	0.00596*
	(0.0719)	(0.117)	(0.111)	(0.0676)	(0.0885)	(0.102)	(0.00336)
Constant	0.600***	0.985***	-0.0215	0.945***	0.306*	0.292	7.72e-05
	(0.136)	(0.193)	(0.189)	(0.122)	(0.183)	(0.214)	(0.00570)

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

In this paper we analysed the wage gap between men and women in the informal sector in Togo. To do so, we used the RIF decomposition method proposed by Fortin *et al*. (2011) for gender wage gaps. We illustrate how our method works by examining the gender wage gap. This is an interesting case to study because the distribution of wages has changed very differently at different points in the distribution, a phenomenon that cannot be captured by summary measures of inequality such as wage variance. Our method is particularly well suited to examine in detail the source of wage differentials at each percentile of the distribution. Our results show that education, work experience and industry are the most important factors explaining observed changes in the wage distribution. However, the wage gap is more pronounced in the first half of the distribution. In other words, discrimination against women has increased in the low and medium quantiles, i.e., it has affected the poorest very much. Furthermore, it is observed that the gender wage gap is mainly due to differences in performance associated with productive characteristics. These results imply that in order to effectively combat the wage gap in the informal market in Togo, emphasis must be placed on those factors that explain the wage difference, namely education, experience and sector of activity.

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2 Subsistence mode of urban housing provision in Tanzania: Analysis of its pattern and challenges for Dar es-Salaam

Juma **Kiduanga** †

Introduction

The socio-economic development of Dar es Salaam is contingent on a wide range of processes that determine the level of the city's competitiveness. According to the Tanzania Development Vision 2025, the concept of competitiveness has been identified as an important attribute for the Tanzanian economy to attain so that it effectively can cope with the challenges of development (URT, 1995: 5). Setting such criterion for Dar es Salaam city to achieve is also imperative because the city is no longer treated as administrative and political centre for resource exploitation of rural sector as it formerly was; influenced by the Dependency and Marxist Centre-Periphery models[2]. The city is

† Institute of Development Studies, UDSM. Tanzania.
☎. +263 (0)54 260 568 / 2482 ✉. jumakiduanga@gmail.com

[2] Scholars of the two models assume that the urban areas referred as core in a developing country do not have a role in developing the rural areas, as periphery ; instead they are exploiting and under-developing them..

used to play a progressive role to the nation in a series of ways. For example, the World Economic Forum (WEF) report 2014 revealed that cities are the engine of productivity growth and essential for the competitiveness of nations and regions.

Of all the processes shaping the city, housing is distinct and has been a strategic tool in making Dar es Salaam become a competitive city. A number of studies have confirmed more positive contribution of housing to development. Kissick *et al.,* (2006) revealed that housing is a key factor in economic, social and civic development. For example, empirical evidence as confirmed by several studies shows that in Dar es Salaam a series of activities rely on housing, including manufacturing, trade and other socio-economic and political activities (Kiduanga, 2012). Housing influences the quality of workers employed in the activities. Also many households use housing to generate incomes. At the urban scale, the planners have been using housing as an instrument for developing the city (Kiduanga, 2006). They have been using houses as a source for tax revenue collection, in order to mobilize the financial resources necessary to pay salaries and to construct roads and build hospitals. The development of housing property has lead into generating employment. Previous studies indicate that housing as it is used effectively to perform a number of functions for instance, poverty and inequality reduction and others is a good indicator for measuring the development level of Dar es Salaam in relation to other cities, both nationally and globally (Mahanga, 2002; Kiduanga, 2012; Awinia-Mushi, 2013).

Factors enabling urban competitiveness have been elaborated in a vast literature. WEF Report (2014: 12) explains the factors in relation to the level of sustainable productivity of a city. The concept of sustainability, according to the report, encompasses economic, environmental and social issues. These sectors, all are important components of the city, to demonstrate efficiency in using available resources for undertaking production. With better quality of products at relatively low cost. The report is however limited in showing the indicators of efficiency when the resources are used to produce goods and services. The concept of efficacy is understood as cost and risks reduction which is attained through effective strategies and policies. The determinant factors for city competitiveness as pointed out by the WEF Report are: policies, strategies and regulations; institutions; hard connectivity; infrastructure, which are considered one of the determinant factors for city competitiveness; and lastly, soft connectivity, which includes factors necessary for boosting technological innovation and distribution. Housing has an important function in urban development, especially in making the city productive, which the literature has empirically verified. For example, Burns *et al.,* (1970) argue that housing is a necessary consumptive good that influence the future welfare of residents. The study has found that the chain of economic impacts of housing does not only end with the direct consumption of its services like water, sanitation and others. By living in better housing, the occupants will perform better at work, which implies increased productivity, output and income. The concept of better housing is understood as adequate housing by the UN Committee on Economic, Social and Cultural Rights. This definition indicates a complete house and acts as a reference for a government to achieve better quality housing through the policies, strategies programmes implemented. The committee has stipulated seven elements as indicated by UN-Habitat (2005: 20-21), which serve as the basis for understanding the concept of adequate housing. First, legal security of tenure. Secondly, availability of services, materials, facilities and infrastructure. The most essential infrastructures for adequate housing are water supply systems, sanitation systems and garbage collection, electricity supply systems, road networks, rain water drainage systems and street lighting. Thirdly, affordability, as housing risk to become too expensive for the occupants. Forth, habitability, for example sufficient space, protection from cold, damp, heat, rain, wind or other threats to health, structural hazards and disease as well as absence of overcrowding. Fifth, accessibility, as adequate housing must be accessible to all members of the community without segregation on the basis of gender, income or vulnerability. Sixth, location; the location of housing should be in areas that allows access to employment opportunities, healthcare, education, childcare and other social facilities. It should not be built on polluted sites or sites liable to hazards such as flooding, landslides etc. Finally, housing must also be culturally adequate implying, that the historical attributes and identity of housing must be preserved when housing is modernized using building materials and the policies supporting the process.

Given the elements above, one may argue that adequate housing can make the city become competitive. When the condition of housing is poor will reduce urban competitiveness, which has been a trend in Dar es Salaam. The city has experienced rapid urbanization concurrent with a high number of subsistence housing, which has created challenges for city competitiveness. This paper looks at such dynamics. It is organized into five sections. Section one is on introduction. Section two examines the conditions made the emergence of subsistence housing provision in Dar es Salaam city. The way subsistence urban housing becomes a challenge for competitiveness of the city is dealt with in section three, while section four focuses on the strategies for improving subsistence urban housing for Dar es Salaam competitiveness. Section five draws the conclusion.

Conditions for the emergence of subsistence mode of housing provision

The task of the following section is to introduce the conceptual and theoretical aspects of housing provision modes. I draw my conceptual framework on the basis of three distinct forms of housing provision stated in the literature. On the basis of building materials used and production process of the housing, the first type of housing is the industrialized form as illustrated in plate 1. This form of housing contributes to accumulation meaning, the increased value is being realized at different stages of production, distribution and consumption/exchange (Burges, 1982 quoted in Ward & Macoloo, 1992: 64). The increased value of housing is conditioned by highly skilled various interest groups and agents creating strong relationships and coordination in the production, distribution and consumption/exchange of property due to available of opportunity. These groups and agents include financial capital, land developers and realtors, construction capital, architects and designers, as well as the state which functions in the form of authorization and regulatory procedures. The use of well remunerated wage labour and capital-intensive technology are important factors for the industrialized housing form to enable the realization of addition value (*ibid.*).

Plate 1. *Industrialized Housing Form*
Source: [Retrieved from]. on 11/7/2015.

Secondly is the manufactured form, a form of housing product that has low labour productivity levels. The manufactured housing form is shown in plate 2. The production is small-scale and often led by a master builder or an architect utilizing labour contracted through personal networks. The design systems are small-scale and the building materials are drawn from both the local manufacture materials as well as from the industrialized sector (*Ibid.*).

Plate 2. *Manufactured Housing Form*
Source: [Retrieve from].

The artisanal or self-built is the third form of housing production. This housing form is shown in plate 3. It is characterized by a lower level of labour productivity than the manufactured form, and according to Gilbert & van der Linden (1987) the artisanal housing has little subdivision of labour. Mobilization of financing, building materials, and management for housing construction process is mainly done by members of the household, and construction works are carved out by skilled and semi-skilled labourers. No architects, engineers or planners are involved. The housing production is, undertaken on an incremental basis, over relatively long duration by the owner located in unplanned human settlements outside formal land development processes and urban planning procedures.

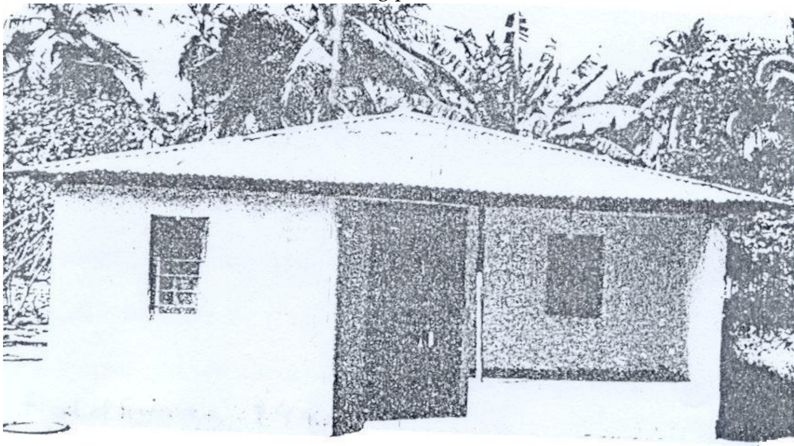

Plate 3. *Artisanal/Self-built housing form*
Source: Pilot Survey done in Chamazi Settlement, Dar es Salaam, July 1, 2015

The concept of unplanned human settlement in the Tanzanian context could also be understood as "informal" or "uncontrolled" human settlement (Burra, 2004). All these features provide conditions for the artisanal housing that often is conceptualized as the subsistence form of housing production. In Dar es Salaam there has been a trend of rapid increase of unplanned settlements accompanied by the subsistence housing form (Kiduanga, 2012). Such kind of housing is also incrementally constructed in planned settlements. The conditions underpinning such situation have been changing depending on the city development (*Ibid.).*

Housing has a long history in the context of urban development of Dar es Salaam. It is a major component of urban human settlements with increasing number of occupants since the beginning of Dar es Salaam as an urban area. Until 1855 the houses located in the settlements were resided by no more than 5000 people (Skaare, 2000). By 1905 the number of houses in the city increased due to increased investments made during the German Colonial Government. The houses were located in racially segregated neighborhoods which accommodated 24,000 people (Skyes & Wade, 1997) of European, Asian and African descents. Following the line of analysis provided by Burgess (1977) one may be able to identify the form of housing each of the three descents occupied and the socio-economic conditions that influenced such pattern. On analyzing forms of housing activities in developing countries and the way they are being organized Burgess has noted they are related with capitalist mode of production and exchange as well as the goal of policies designed. According to Burgess this takes place at all levels of production, consumption and exchange and forms of housing meeting the capitalist goals. At the level when houses are complete housing policies and the laws designed are unable to go beyond or contradict capitalist goals.

The German Colonial Government designed urban development plan to guide the growth of Dar es Salaam in order to serve the interest of colonial regime and suppress the Africans in all aspects of urban development. In housing sector the indigenous residents were segregated and left to build houses of low standard and were treated as temporary residents while the Europeans were provided better housing. The British Colonial Government continued with the same policy. For example, the planning legislation of 1956, as noted by Mkama (1970), excluded many Africans in the provision of good housing. While the non-Africans were provided with better housing, the Africans, who were the majority, were provided low standard of houses in overcrowded and poor sanitary conditions.

The housing inadequacy was not immediately reversed after independence, but instead increased. From 1963 to 1967 the houses of poor condition increased by 70% from 7000 housing units recorded in 1963 (URT, 1968). The condition was influenced by absence of a strong and clearly defined institutional framework capable of providing a road map for the future of housing. The government's First-Five Year Development Plan (1964-1969) contributed little to urban housing development because of its focus on development in the rural sector. The subsequent strategy of housing cooperatives, put in place was likewise unable to solve the housing shortage in the city. Rental housing tenure – though is high in demand due to the rapid urbanization was not much supported by the strategy of socialism. Other limiting reasons, as noted by the 2000 National Human Settlements Development Policy (URT, 2000: 14), were (i) lack of a clear government policy on how housing co-operatives should operate; (ii) institutional constraints, especially when it comes to the allocation of scarce surveyed plots and building materials; (iii) inadequate assistance from the government; (iv) poor administration and; (v) lack of competent and honest leadership.

Since the late 1960s there has been a rapid increase of buildings in unplanned settlements. Between 1967 and 1973 the number of buildings in unplanned settlements increased by 28,000 units from 11900 units recorded in 1967. In 1980 the settlements were 25. By 1992 the settlements had increased to 40, and by 2002 to 56. According to Matemba (2011) 75% of the areas in Dar es Salaam are unplanned and 25% are planned. The percentage of housing units located in unplanned areas was 80% out of 500,000 housing units in the two different areas in Dar es Salam. Housing could be considered the second greatest challenge, after traffic jam, faced by the city (Mhache & Mauma, 2013).

The challenge is caused by two factors. First, the inability of institutional framework to tackle housing shortage. A second factor is associated with Turner's ideas, as noted by Kool *et al.*, (1989) have influenced many governments of developing countries including Tanzania to put in place policies for solving housing problems facing the poor by including what they have. What Turner proposes is that instead of condemning and threatening the existing potentials of the poor as utonomous systems governments should respect them and guide them where necessary (Kool *et al.*, 1989:187-188).

In Dar es Salaam many individuals make their own efforts in achieving housing. It takes long and is constructed incrementally once the individuals get the resources. Finance is the most important resource. A number of studies for instance, that of Kiduanga (2004) done in Dar es Salaam confirmed that finance determines the quality and structure of housing as well as influences the pace of completing housing construction. A study conducted in Bangladesh, Ghana and Zimbabwe highlights that households are considerably delayed to extend their houses because of difficulty of mobilizing finances (Tripple, 2000). According to Benjamin *et al.*, (1985) the majority of low income housing in Indonesian cities are built gradually and takes long time to be completed because of irregular availability of finance to low-income house owners. Many households in Dar es Salaam have built their houses using finance obtained out of savings from personal incomes. After mobilizing the finance many urban residents buy land in unplanned areas controlled by customary land tenure. After land and building materials have been purchased the construction takes place. Construction of the physical dwellings is done by *fundis* (craftsmen) hired by the house owners, while the participation of house owners in the construction include the organization, supervision, supply of building materials and negotiation of prices with various *fundis* who have house construction skills. Usually the payment of *fundis* takes place after the house owners are satisfied with the quality and quantity of work. A number of studies found that the supervisory role by house owners in the construction process is essential for keeping the costs under control and minimizing the extent of cheating common among the majority of *fundis* in Dar es Salaam (Kiduanga, 2004; Lusanga, 1993)

Due to the shortage of finance the majority house owners purchase materials in very small quantities (Kiduanga, 2004), delaying the completion of houses. Moreover, the construction is on incrementally basis and is taking place long period because of financial problem facing house owners. The average construction period of a house structure which does not have better infrastructure such as sewage systems, roads etc. is 8 years (Kiduanga, 2012). Many households assess the houses they own are worth value despite they build incrementally and takes long period through their own efforts. For example, keeping households out of debt and encourage finalization of their houses in order to make them livable. The households create wealth because the urban land they possess holds high value.

The ways subsistence urban housing becomes a challenge for competitiveness of the City

In order to explain the way subsistence housing form becomes a challenge for city competitiveness there is a need first to conceptualize housing and city competitiveness. The concept of housing entails the range of functions it performs to people or nation or city. City competitiveness is demonstrated by its capability of attaining a number of goals, including cost and risks reduction, increasing real income, improving the life of citizens, realizing better quality social services, proper and optimum, effective and efficient use of resources in a sustainable manner[3]. Better quality of housing is an instrument for making the city productive and capable to achieve above stated goals. Unlike the case of incremental housing, the city's competitiveness is relatively little affected by this kind of housing which is inadequate in terms of quality and quantity. The physical structure of the housing is incomplete with poor condition of service facility and unreliable secure title. Clean and safe water are other of elements of better quality of urban housing. Empirical studies have shown that many houses in unplanned settlements have inadequate water (Kiduanga, 2012). Many people living in the houses located in unplanned settlements depend on wells to access water. During rain seasons water fetched from the wells is unsafe, unclean and is a major source of borne diseases such as cholera, dysentery, typhoid and amoebaean (Lyimo *et al.,* 2007). During outbreak in unplanned areas, densely inhabited, is a challenge to the city because the lives of affected residents are threatened, hence they will no longer work and productivity drops.

Adequate sanitation facilities provision is another indicator of better quality housing. However, services are poorly delivered both in planned and unplanned areas (Mnaka, 2012). The city's planning agencies have been unable to keep pace with the rapid daily generation of the wastes in the city areas. The problem has been persistent and is a great challenge for city competitiveness. For instance Mnaka, (2012) reveals that Dar es Salaam was ranked by Forbes the 12th in a list of 25 dirtiest cities in the world in 2008. Lack of effective national policies on waste management and monitoring waste management activities by the responsible institutions have been cited to be the major factor perpetuating the problem (*Ibid.).* Urban sprawl is another problem facing the city, caused by horizontal and haphazard housing expansion. The housing expansion made haphazardly associated with incomplete

[3] These are among the goals defining the city capability and competitiveness when it will achieve them.

house structures and areas of poor land-use plans - cause various problems in the city. The problems are such as increased costs for supplying social services, electricity and infrastructure; managing wastes and difficult to access the houses for providing service during fire outbreak (Kiduanga, 2013). Making comparison between two cities based on the quality of housing can be made for reasons of knowing how the two cities compete in a number of issues. For instance, a study by Alawi (2015) found that. Many residents in Dar es Salaam and Kampala rely on renting houses for accommodation. Empirical findings indicate rental costs incurred by resident are higher in Dar es Salaam than in Kampala. The average resident in Dar es Salaam spend 34.1 per cent of the monthly earnings on renting accommodation, while in comparison, in Kampala the percentage is 13 per cent (Alawi, 2015). Land, finance, construction management and housing market are important factors for housing development. The costs of these factors affect in different ways the costs of housing development in the two cities. When a house of a two-bedroom unit in Dar es Salaam is sold at US$ 26, 913, in Kampala the price of property with the same size is US$ 74,956 (Isaa, 2014). The difference is due to land prices and Value Added Tax (VAT). In Kampala the average price of one acre of land in prime areas are higher (i.e. US$ 37, 478) than in Dar es Salaam (US$ 10,000). In Kampala the VAT charged for a house is 18 per cent, while in Dar es Salaam the VAT is 15 per cent. The cities commercial banks charge same interest rates on mortgage loans for financing housing, which is between 15 and 20 percent. The number of days spent to request, approve plans and issue building permit is however not the same. In Dar es Salaam it takes in average 205 days while in Kampala one can on average expect to spend 60 days waiting for the process to pass from request and approval of plans in order to receive buildingpermit (Isaa, 2014; Alawi, 2015).

Strategies for improving subsistence urban housing for Dar es Salaam competitiveness

The strategies put in place for improving housing conditions varies in form, each specifically addresses the housing problems facing Dar es Salaam. As the urban context changes due to population increase, the housing problem attains a multidimensional character. This phenomenon demands a partnership of various sectors for attaining adequate housing, essential for competitiveness of the city. The contribution of strategies developed to improving the housing condition for enhancing city's competitiveness in terms of the population living in a better life are examined as follows.

Strategies for upgrading the unplanned settlements

The strategies for upgrading unplanned settlements are intended to bring positive effect on the conditions of unplanned settlements and urban housing inhabited by the poor who comprise the majority in the city. The settlements and housing lack following features, which are essential for the residents in order to live in a better life: (i) provision of basic infrastructure and services such as access roads, streets, footpaths, drainage, sanitation, electricity, water supply, solid wastes collection, schools, health centres, and markets; (ii) implementing regularization schemes, including the recording, adjudication, classification and registration of occupation and land use by the residents and those working in the settlements (UN-HABITAT, 2010); (iii) promotion of income-generating activities through micro-finance schemes; and (iv) home improvement (Rasmus, 2005). The implementation of the strategies of upgrading unplanned settlements has taken place in different periods of time in accordance with following model:

2 Project of sites and services, slums and squatters upgrading

The first model was a major project implemented by the government in two phases with the assistance of the World Bank. Phase one of its implementation reached from 1974 to 1977 and involved the provision of about 10,000 serviced plots and upgrading a further 11,000 houses in squatter settlements in Dar es Salaam, Mwanza and Mbeya. The second phase of the project was implemented between 1977 and 1984 in Dar es Salaam, Morogoro, Tabora, Iringa, Tanga. The project under the second phase estimated that the squatter upgrading would benefit about 315,000 people, representing about 26% of the Tanzania urban population. The surveyed plots were estimated to provide about 75% of the residential building land required up to the year 1981 (Mghweno, 1984). The project was implemented under three major principles; affordability, cost recovery, and replicability. The affordability principle implies that the project must provide a package of benefits that is widely acceptable and affordable by the beneficiaries. The charges must be in form of small mortgage repayments not generally exceeding 20 per cent of the households' income of the targeted residents. Cost recovery and replicability imply the cost of the projects must, to a great extent, be recoverable and capable of being replicated to meet the demand of others for urban housing and community services (Adepoju *et al.,* 1989). The policy instruments for the project's implementation were zoning regulations, building standards, land tenure, pricing, taxes, financial institutions, building materials, industry, and construction technologies (Matemba, 2011). Studies carried out to assess the performance of the project show that many of its objectives were not attained because of failure to recover the costs of running the project (Kaare, 1998; Materu, 1986). Also the sustainability of the project and poor participation contributed to the ineffectiveness of the project. According to UN-HABITAT (2010) the project used a top-down approach. At the time local governments, crucial for strengthening participatory planning, was non-existent until 1982 when they were re-introduced. Projects implemented during the reintroduction of local governments however allowed community members and the private sector to participate and make decisions. Finding indicates that following their low capacity level, their performance of participation and decision making was poor (UN-HABITAT, 2010).

Enabling housing strategies

The enabling strategies were put in place as alternative approach for addressing the housing problem following the projects of 1970s and early 1980s, were unable to bring significant positive impact on housing sector in Dar es Salaam and other urban areas in and outside Tanzania. The projects were limited due to their focus on improving certain components of the unplanned settlements, thus leaving out the wide political, social and economic sectors. The enabling strategies as an approach to housing problem is underpinned by an understanding that housing is a broad concept linked to a wide range of issues and not only those where the housing is located but also those in other countries. Viewed in this broad perspective, the developed enabling approach advocates the collective efforts of various actors as a panacea for solving the housing problem. The various actors that have to be involved in solving the housing problem are governments at central and local governments, private sector, civil society organizations, the community and the international organizations. The role of each of the actors forming the partnership in the effort of solving the housing problem has to be defined basing on comparative advantage. The government, in forging the partnership, has the role of providing enabling conditions for other actors to contribute efficiently and effectively towards achievement of adequate housing for all (UN-Habitat, 2006). The contribution of other actors can be in a number of forms. For instance, the CSOs, the private sector and community can work with the government in a country to revise and or formulate housing policies while the international organizations may provide financial support for housing development. The emphasis for governments of member countries of the United Nations to apply the enabling approach for solving housing problems took place in 1988 when the United Nations General Assembly adopted the Global Strategy for Shelter to the Year 2000.

In 1992 at the International Conference on Environment and Development organized by United Nations in Rio de Janeiro, 178 Governments including that of Tanzania agreed to implement the following eight programmes through the enabling approach for achieving sustainable settlements development: provide adequate shelter for all; improve human settlements management; promote sustainable land-use planning and management; promote the integrated provision of environmental infrastructure: water, sanitation, drainage and solid waste management; promote sustainable energy and transport systems in human settlements; promote human settlement planning and management in disaster-prone areas;. promote sustainable construction industry activities, and; promote human resources development and capacity for human settlements development (UN-HABITAT, 2006). Housing adequacy is one of the important aspects of sustainable settlements development to be achieved through implementing the eight programmes. In Tanzania there have been strategies undertaken to attain it under the implementation of the programmes. According to (URT 2011: 16-20) these include the strategies of (a) creating a conducive environment by both the central government and Local Urban Authorities (LUAs) for developing diverse real estate developers; (b) strengthening the institutions involved in research activities on appropriate and affordable building materials and housing technology. These strategies intend to encourage housing tenure development and access to housing by people from all income categories; (c) establishing and building capacities housing sections and departments from local to central government levels for effective housing development management. The strategies put in place for increasing housing finance include amending the Mortgage Finance Act (2008) and the Unit Title Act (2008) to become effective; providing support of government and LUAs to housing finance institutions of large, medium and small sizes in the area of mobilizing enough finance. Prevention of unplanned housing development is realized through the strategy of strengthening collaboration between local community leaders, central government and LUAs to guide, regulate and monitor land development. In Dar es Salaam, through the enabling approach, a number of projects have been implemented to promote sustainable human settlements development. These include the Sustainable Dar es Salaam Project (SDP), the Community-Managed Upgrading Project, such as the upgrading of Hanna Nassif (Jenny, 2006).

Enabling is a viable and effective approach because it involves a broad range of sectors in solving the housing problem in a partnership, as well as contextualizing the problem. To make the approach more effective and to improve the subsistence housing form of provision in the city the following recommendations are made: (a) the government should give more support to the development of real estate developers; (b) the level of compliance with laws and policies guiding city's development should be enhanced (c) the housing construction on an individual basis should be avoided.

Conclusion

The paper concludes by arguing that adequate housing is a strategic input for cities, such Dar es Salaam, to become more competitive. Such link exists because adequate housing attains better performance of any activity undertaken in a city. Findings reveal that housing of subsistence form in Dar es Salaam has dominated. Though such situation is not wasteful, it has created a challenge of reducing the high degree of city's competitiveness. The paper calls for improving the subsistence form of housing through enabling approach for Dar es Salaam to become a strongly competitive city.

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3 Predicting South African personal income tax –using Holt–Winters and SARIMA

Mangalani Peter **Makananisa** [a] [†]
Jean Luc **Erero** [b]

Introduction

Persistent income inequalities in the Eastern Cape have led to the realisation that growth could be unbalanced, non-inclusive and unsustainable. The post-recession low growth path and declining economic activity have negatively impacted employment creation and government revenue collection. Consequently, high levels of unemployment (especially among the youth) and the fiscal ceiling have not only prevented the quest for all-inclusive, equitable and sustainable economic growth, but have also disturbed the structure of government expenditure in terms of economic growth (Robinson, 2017). Following this, the question

[a†] South African Revenue Service, Operational Research, Pretoria, South Africa.
☎. +2782 4564669 ✉. pmakananisa@sars.gov.za
[b] Department of Quantitative Techniques University of Yaounde II South African Revenue Service (SARS), South African Revenue Service (SARS). Pretoria, South Africa
☎. +237 717 918 41 ✉. JErero@sars.gov.za

then is how to achieve a pro-poor growth in the province. Put differently, how do we ensure that an additional national income reaches the targeted group of people? This is important because fiscal policy makers would not only need to be informed on the growth impact of their initiatives but also on their poverty, employment and other social impacts.

Fiscal policy promotes growth through macro and structural tax and expenditure policies. At the macro level, it plays an important role in ensuring macroeconomic stability, which is a prerequisite for achieving and maintaining economic growth (IMF, 2015). At the micro level, through well-designed tax and spending policies, it can boost employment, investment, and productivity. Fiscal policy is a powerful instrument used to assess government revenue, government expenditure, budget balance and borrowing requirements. The tool reveals more about a country's development strategy. Its redistributive effects, equity promoting and the progressive nature of the tax system make the policy more appropriate to address poverty and inequality than probably any other area of policymaking (National Treasury, 2017). The robustness of fiscal policy must be assessed.

Through a scientific quantitative approach (such as the Social Accounting Matrix), it will be possible to measure the economy-wide impact of say, an additional R1 increase in government revenue on households of different income, race, gender, occupation and age groups. The Social Accounting Matrix (SAM)[2] model will be used to simulate the impact of a fiscal expansion, through a hypothetical 1% increase in government expenditure and its effects on growth, employment, poverty reduction, investment and productivity.

The SAM is a well equipped tool for analysing the socioeconomic impact of any government project. It is used to build economy-wide macroeconomic models explicitly designed to analyse the distributional impacts of policy change and to respond to questions such as the following:

[2] For more information on SAM models, see articles by Pyatt & Round (1985), Reinert & Roland Holst (1997), Pyatt (1988), Thomas & Thurlow (2009), and Robinson & Roland-Holst (1988).

- What informs the choice of government strategic programmes and initiatives? What is the socioeconomic impact of an infrastructure project or investment? How do government programmes affect employment and compensation of employees (CoE), output, gross value added (GVA), gross operating surplus (GOS), investment, trade, poverty and inequality, and other socioeconomic variables?
- How does government ensure that an additional R1 in the fiscus reaches the targeted people? Who benefits from economic growth?
- To what extent do government policies, strategies and initiatives contribute to the achievement of government goals? What determines the robustness of a policy or strategy?
- Micro-simulations: To what extent are households affected un-uniformly by the external economic factors, such as oil price increases, recession? How are people of different (i) gender, (ii) race, (iii) income group, such households with no income, (iv) age group, such as youth, (v) people of different skill level or different professions, etc. affected?
- What is the economy-wide impact of 1% change in: government expenditure, taxes, government revenue, export, household income, investment or FDI on macroeconomic variables such as growth and employment?

The applications of the SAM model at sectoral level are designed to achieve the following purposes: Firstly, to identify industries and sectors with high comparative and competitive advantages; to determine inter-industry impacts through multipliers, to assess backward and forward linkages; and lastly, to assess the number of jobs sustained per sector through infrastructure projects (Eurostats, 2008).

There is little national literature on modelling of tax revenue, specifically looking at the personal income tax of South Africa. Hence, this independent study will focus on modelling and forecasting the South African PIT using time series model. This will assist the South African authorities in deriving the forecast which are more precise and unbiased. Therefore, it will improve the decision making for future PIT revenue management.

The national literature includes the work of Van Heerden (2013) focusing on the PIT structure and its implication on individual tax revenue in South Africa. She used a micro-simulation tax model to determine what can be done to optimise individual taxes so that they can minimise the negative burden of taxation on the performance of the economy. The author found that lowering tax rates stimulates potential for improved levels of efficiency with tax burden.

Boonzaaier (2015) tested the possible tax revenue asymmetries relative to the business cycle via a smooth transition ARMA framework. Its model allowed for the estimation of two separate regimes, i.e. a low and high growth regime where the movement in tax revenue at all times should be governed by a weighted average of two different linear models. The findings indicated that tax revenue collections do react differently depending on whether it is in a high or a low growth phase impacting revenue forecasting process and calculation of cyclically adjusted budget balance. Conversely, the study did not include the out of sample forecast given the impact of the cyclical changes (higher or lower grow phases).

Over estimation and under estimation of tax revenue results in an unstable economy and unreliable statistics in the public domain. The burning question might be which types of model(s) can better predict/forecast variable(s) of interest. Every model has some advantages and disadvantages. Nonetheless, they depend on the use of the models becauseexplanatory models are good for sensitivity analysis while time series are limited for sensitivity analysis. In fact, the later minimises biasness when forecast are made.

The aim of this paperis to find a suitable SARIMA and Holt–Winters model that suits the sample monthly data for PIT well enough, from which a forecast can be generated. The R-statistical software was used for modelling and forecasting purposes. In this respect, we attempted to forecast South Africa's PIT using the mentioned methods because they have not been explicitly applied in a South African context for tax forecasting and publication purposes. Section 2 presents the literature review. Section 3 described the PIT historical contribution to total taxand the methodology is presented in section 4. Section 5 shows the models application and results on PIT, and section 6 discusses model results and limitations. Conclusions and recommendations are provided in sections 7.

Literature review

Various literatures around the world support the use of time series models. Some of the literatures on the ARIMA/SARIMA and Holt–Winters time series models include the work of Jayesekara & Passty (2009). These authors used ARIMA models, including the dummy variables for seasonal adjustment, as aunivariate benchmark model to forecast the net income tax revenue in Cincinnati City. The monthly data were obtained from the Cincinnati Income Tax Division (CITD) for the period January 1970 to April 2009, although the data used to carry out the estimation were reduced to start from January 1989 due to changes in taxrates. In order to reach the two final ARIMA models, the best fit models were selected based on the model with minimal Akaike Information Criterion (AIC), the minimum Root Mean Squared Error (RMSE) and the model with the highest R-Squared (R^2).

The ARIMA models fitted predicted the Cincinnati net income tax well, captured the seasonality in the data through out the sample used, and the within sample estimates were compared with the actual for the period 2006 to 2009. Furthermore, the ARIMA model was considered to forecast the net income tax starting from January 2008 (a portion of the in-sample) to verify the effectiveness of the model. Moreover, data were converted to bi-monthly in order to construct a bi-monthly model. In this respect, Jayesekara & Passty (2009) recommended the use of ARIMA for the CITD for short-term forecasts of net income tax.

Similarly Chatagny & Soguel (2009) used the ARIMA model to estimate tax revenues (an amalgamation of PIT and Corporate Income Tax (CIT)) for all 28 cantonsor districts in Switzerland. The main aim of the study was to prove that forecast bias can be reduced by using univariate time series models. Tax revenue data for the period 1944 to 2006, together with the observed official forecasts were obtained from the districts. In addition, the time series data were divided into two samples (1944 to 2006 and 1976 to 2006) due to some districts not having recorded historical data in certain years. To assess the ARIMA performance against the observed forecasts for the two sample periods, the mean percentage error was used to classify the over, under and zero error percentage on district. The results from the mean percentage error showed that the observed forecasts under estimated tax revenue in almost all cant on sand ARIMA models hada Mean Percentage Error (MPE) close to zero in thet wo sample periods. The study concluded that bias from an observed forecast can still be reduced by using simple univariate models, ARIMA.

Pelinescu, Anton, Ionescu, & Tasca (2010) analysed the Romanian local budget with the aim of assisting officials to create efficient plans and manage cal income and expenditure using a good strategic management tool. This arose as a result of the local authorities finding it difficult to predict future revenues to construct their annual budgets. Using the historical data from the first quarter of 2000 to the third quarter of 2010, the authors applied the Holt–Winters multiplicative and additive models to forecast total local revenue and own revenue of local authorities. The E-views software was used to build and run the Holt–Winters equations and to select a model that minimised the Root Mean Squared Error (RMSE). The study recommended the use of a Holt–Winters model as a tool for multi-annual budget forecasting because it is user-friendly and provides stable forecasts.

A similar study was conducted in Romanian by Brojba, Dumitru, & Belciug (2010) who used ARIMA models on monthly earning data for the period 2007 to 2008 (the economic crisis period) to model the total budget revenue. The ARIMA models captured the data movement during the economic crisis because the data contained or showed the trend and seasonality. The fitted values were close to the actual and the study concluded that ARIMA models can be used to set targets and sound future developments. Nonetheless, the models have its limitations as the parameters are sensitive to sample selection, with the most accurate forecasts being for the short-term.

Forecasting future revenue with maximum precision is important for country's economy, as it leads to a better overall distribution of future budgets. From the above literature review it can be seen that time series models have proven to be useful methods for forecasting tax revenues. These types of methods are more precise for short-term forecasts (two to three years) because their precision declines over a longer period.

More knowledge on the variables of interest must be obtained when generating long term forecasts because they are precise, and the model must be well defined, and some statistic must be considered. These statistics aresuch as root mean squared error, mean absolute percentage error, Akaike information criterion, and many others. The following section summaries the SARIMA and Holt–Winters models theories and assumptions.

PIT historical contribution to total tax

South African PIT is a tax levied on the taxable income (gross income less exemptions and allowable deductions) of individuals and trusts. It is determined for a specific year of assessment. Taxable capital gains form part of taxable income. Most individuals receive their income as salaries or wages, pension or annuity payments, and/or investment income (interest and dividends). Some individuals, such as sole proprietors and partners, may also have business income which is taxable as personal income.

This main source of revenue (PIT) is made up of sub sources such as employee's tax (or pay as you earn), provisional tax and assessed tax with employees tax contributing around 95% and the other two sub sources sharing the remaining 5% of PIT. The employee's tax is collectable by employer on behalf of employee, hence provisional tax payable by any person who derives income other than remunerations, an allowance or advance and assessed tax paid on final assessments of the tax return (SARS, & National Treasury, 2017).

PIT remain the largestsource ofthe South African revenue with its contribution to total tax of 40.2% in 1995/96 hence its relative contribution has declined to 37.2% in 2016/17 SARS fiscal year (Figure 1). This tax is levied per tax brackets from which the tax payer belongs to with regards to their generated income per specific period (SARS, & National Treasury, 2017).

Figure 1 shows the contribution of this main source of revenue (PIT) to the total tax revenue for the period 1995/96 to 2016/17 fiscal years.

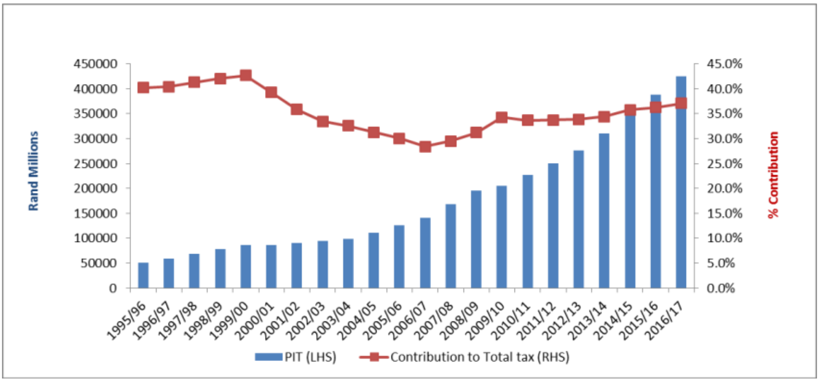


Figure 1. *Personal income tax and its contribution to total tax*
Source: SARS, & National Treasury (2015, 2016 & 2017).

Research methodology

The Time Series Regression methodology is seen as the basis for modeling and forecasting the quantitative variable(s) of interest as their forecast are unbiased. Thuse very thing that is needed to project the continuation of the historical pattern is already included in the history of the variable. Here, more weight is given to the recent data in this study. The three popular Time Series Regression methods– Holt–Winters Model, SARIMA Model and the Time Series Regression with ARIMA error were used to predict South Africa's PIT revenues.

Holt–Winters model

Holt–Winters methods are an extension of simple exponential smoothing and Holt's trend corrected exponential smoothing method. Simple exponential smoothing is used to forecast series when there is no trend or seasonal pattern, while Holt's trend corrected exponential smoothing is applicable when a time series displays a changing level (mean) and the growth rate (slope) for the trend. However, work on state space models with a single source by Hyndman, Koehlor, Synder, & Grose (2002) provided a statistical framework for the exponential smoothing methods. Holt–Winters methods are designed for a time series that exhibits a linear trend and seasonality. These methods include the: additive Holt–Winters model and multiplicative Holt–Winters model. However, this study will concentrate on the additive Holt–Winters model.

Let $y_t = y_1, y_2, y_3, \ldots y_T$ be the time series of interest where $t = 1,2,3,\ldots T$. The additive Holt–Winters models is appropriate when a time series y_t has a linear trend with an additive seasonal pattern for which the level (mean), the growth rate and the seasonal pattern may be changing (Hyndman, *et al.,* 2002). This model can be described as:

$$y_t = (l_t + tb_t) + s_t + e_t \tag{1}$$

Where l_t is the mean (level value), b_t the growth rate, and s_t is the fixed seasonal pattern at time t. The additive Holt–Winters method can be summarised as follows.

Suppose that the time series $y_t = y_1, y_2, y_3, \ldots y_T$ exhibits linear trend locally and has a seasonal pattern with constant (additive) seasonal variation and the level, growth rate and seasonal pattern may be changing. Then, the estimate l_t for the level, the estimate b_t for the growth rate and the estimate s_t for the seasonal factor of the time series in time period t are given by the smoothing equation:

$$l_t = \alpha(y_t - s_{t-1}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{3}$$

$$l_t = \alpha(y_t - s_{t-1}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{4}$$

Where α, β and γ are smoothing constants between 0 and 1, l_{t-1} and b_{t-1} are estimates in time period $t-1$ for the level and growth rate respectively, and s_{t-1} is the estimate in $t-1$ for the seasonal factor. The application of this method requires that a time series have a linear trend with an additive seasonal pattern.

The Additive Holt-Winters requires initial values for l_t, b_t and s_t which are estimated as follows:

$$l_0 = \frac{1}{s}(y_1 + y_2 + \ldots + y_s), \tag{5}$$

$$b_0 = \frac{1}{s}\left[\frac{y_{s+1} - y_1}{s} + \frac{y_{s+2} - y_2}{s} + \ldots + \frac{y_{s+s} - y_s}{s}\right] \tag{6}$$

$$s_1 = y_1 - l_0, \tag{7}$$

$$s_2 = y_2 - l_0 \tag{8}$$

and

$$s_s = y_s - l_0 \tag{9}$$

where smaller s is the number of seasons.

The forecast at time period T+$\wp$ will be given by:

$$y_{T-\wp} = l_T + \wp b_T + s_T, \tag{10}$$

Where l_T the smoothed estimate of the level is at time T, b_t is the smoothed estimate of the growth at time T and s_T is the smoothed estimate of the seasonal component at time T.

SARIMA model

The SARIMA model relates the current time series observation to its historical seasonal occurrence; this is called model fitting. This means that the series to be forecast is generated by a random process with a structure that can be described. The description is given in terms of the randomness of the process rather than the cause and effect used in regression models (Pindyck, & Rubinfeld, 2010). For this type of model the data must be stationary around the mean and the variance.

Let $y_t = y_1, y_2, y_3, \ldots y_T$, be the time series of interest where t = 1, 2,..., T, and $w_t = \nabla_s^D \nabla^d y_t$ be the stationary variable derived from y_t, then the general SARIMA equation is represented by equation 11 (Shumway, & Stoffer, 2006).

$$\Phi_P(B^s)\phi_p(B)w_t = \delta + \Theta_Q(B^s)\theta_q(B)\eta_t \qquad (11)$$

Where $w_t = (1-B^s)^D(1-B^d)y_t = (1-B^d - B^{sD} + B^{sD+d})y_t$ are the product of seasonal differencing D and non-seasonal differencing d, s is the series seasonality which takes the value 4 for quarterly time series data and 12 for monthly time series data, $\phi_p(B) = 1-\phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ are the non-seasonal AR components of order p, $\Phi_P(B^s) = 1-\Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \phi_P B^{Ps}$ are the seasonal AR components of order P, $\theta_q(B) = 1+\theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q$ are the non-seasonal MA components of order q, $\Theta_Q(B^s) = 1+\Theta_1 B^s + \Theta_2 B^{2s} + \ldots + \Theta_Q B^{Qs}$ are the seasonal MA componentsof order Q, δ is the constant term and η_t the disturbance or error termat time t, and B is a back shift operator with $B^i(w_t) = w_{t-i}$ and $B^j(\eta_t) = \eta_{t-j}$.

The Autocorrelation Function (ACF) which is represented by ($\hat{\rho}_k$) at lag k provides a partial description of the process for modelling purposes (Pindyck, & Rubinfeld, 1998). This is useful for the selection of the autoregressive and moving averages components and is given by:

$$\hat{\rho}_k = \frac{\gamma_k}{\gamma_0} = \frac{\sum_{t=1}^{T-K}(w_t - \overline{w})(w_{t+k} - \overline{w})}{\sum_{t=1}^{T}(w_t - \overline{w})^2} \qquad (12)$$

A better way to check model adequacy is to analyse the residuals of the series obtained from the model. If the model is correctly specified and the parameters are reasonably close to the true value, the residuals should have nearly the properties of white noise. This means that they should behave more or less like independent, identically distributed normal variables, with zero mean and common variance. Hence, the residuals will be stationary in both the mean and variance. The most popular residual diagnostic to check for the models adequacy is the Ljung–Box (LB) statistic, which tests for the joint hypothesis that all the $\widehat{\rho}_k$ (autocorrelation) up to a certain lag are equal to zero. The LB test statistic in equation 3.13 follows a chi-square (χ^2) distribution with m degrees of freedom for larger sample n.

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{\widehat{\rho}_k^2}{n-k}\right) \tag{13}$$

Time series regression with SARIMA

The regression model with SARIMA error is simply the expansion of a linear regression model. Since variables are recorded over time interval, the dependent and independent variable(s) should be stationary for the simplification of the model fitting. The linear regression will take the following form:

$$\nabla^d y_t = \beta_0 + \sum_{i=1}^{l}\beta_i(\nabla^d x_{it}) + e_t \tag{14}$$

Where ∇^d is the stationary differencing of order d , y_t is the variable of interest at time t, x_{it} is the i^{th} explanatory variable at time t, at the error term at time t, β_0 and β_i represent the constant termand the coefficient of the i^{th} explanatory variable, respectively. The error term from the model fitted assume that there is autocorrelation within the currentet and the previous errors ($e_{t-1}, e_{t-2}, e_{t-3},\ldots$) and the ARM A model can be fittedandbe mathematically represented as follows (Hyndman, Makridakis, & Wheelwright, 1998):

$$e_t = \frac{\Theta_Q(B^s)\theta_q(B)}{\Phi_P(B^s)\phi_p(B)}\eta_t = \Phi^{-1}{}_P(B^s)\phi^{-1}{}_p(B)\Theta_Q(B^s)\theta_q(B)\eta_t \tag{15}$$

When the assumption hold, the model is now called Time Series Regression with SARIMA error and can be represented as follows:

$$\nabla^d y_t = \beta_0 + \sum_{i=1}^{l} \beta_i (\nabla^d x_{it}) + \Phi^{-1}{}_P(B^s)\phi^{-1}{}_p(B)\Theta_Q(B^s)\theta_q(B)\eta_t \quad (16)$$

The SARIMA fitted on the error tern e_t is naturally expected to further reduce the unexplained part of the variation in e_t to η_t, thus $\eta_t < e_t$ resting in more accurate fitted/predicted values.

Some measure of accuracy

For a given time series, there may be several competing models for forecasting. According to Wei (2006), the models can be compared for goodness of forecasting using the criteria described below. Fit the models to the $t-1(0<l\le t)$ observations of the time series and use the fitted models to forecast the last l observed values of the series, we can calculate:

$$e_t(t-l+j) = y_{t-l+j} - \hat{y}_{t-l+j},\ j = 1,2,...,l \quad (17)$$

Where for $j = 1,2,...,l$, $\hat{y}_{t-l+j}$ is the forecast for y_{t-l+j} using any competing models; and compute:

$$PE = \frac{e_t(t-l+j)}{y_{t-l+j}} * 100, \quad (17)$$

$$MPE = \frac{1}{l}\sum_{j=1}^{l} \frac{e_t(t-l+j)}{y_{t-l+j}} * 100, \quad (18)$$

$$MAPE = \frac{1}{l}\sum_{j=1}^{l} \left| \frac{e_t(t-l+j)}{y_{t-l+j}} \right| * 100, \quad (19)$$

$$MSE = \frac{1}{l}\sum_{j=1}^{l} e_t^2(t-l+j), \quad (20)$$

$$MAE = \frac{1}{l}\sum_{j=1}^{l} | e_t(t-l+j) | \quad (21)$$

The best model with in the method for forecasting is the one with the smallest Mean Percentage Error (MPE), Mean Square Error (ME), Mean Absolute Error (MAE) or Mean Absolute Percentage Error (MAPE) depending on the criterion/criteria which one chooses to use. The otherpopularcriteriaused to select the best fitting model(s) is the R^2 which can be represented by equation 23, although R^2 is commonly used for explanatory models.

$$R^2 = \frac{\sum_{i=1}^{T} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{T} (y_i - \bar{y})^2} \tag{23}$$

Two commonly used criteria for choosing the best model, according to Maindonald & Braun (2003) are the Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The AI C is defined by the following equation.

$$AIC = -2\ln(Likelihood) + 2r \tag{24}$$

The AIC increases with the number of model parameters (r), and the best model has the smallest AIC. The BIC is an extension of the AIC and is given by:

$$BIC = -2\ln(Likelihood) + r\ln(T) \tag{25}$$

Where T is the number of observations in y_t. As with the AI C, the best model among competing models within the method has the smallest BIC.

Model application and results on PIT

The initial sample data from quarter 1, 1995 to quarter 1, 2017 in section 4 was divided into two samples, quarter 1, 1995 to quarter 1, 2014 andquarter 2, 2014 to quarter 1, 2017 for model training (fitting) and model testing (prediction) purposes, respectively.

Moreover, the models out of sample forecast were generated for the period quarter 2, 2017 to quarter 1, 2020.

We can recall that the purpose of the study is to model and generate annual or Fiscal Year (FY) forecast for PIT. Normally, the FY span for SARS includes a fixed period starting from April to March for each year. This implies that the quarterly fitted/ predicted values will then be aggregated to form FY fitted/ predictions and be compared with the PIT actual for the corresponding FY which apply to the out of sample forecast. The following section summarises head dative Holt–Winters model fitted and the results there of for personal income tax.

PIT additive Holt–Winters model

Unlike SARIMA models, Holt-Winters models look at a time series data of interest, separated into three components which are the level value, trend and seasonal. This model gives each component's weight on an interval of zero to one, which should be able to fit the model and forecast the future values. The PIT time series has a gradual increasing trend and an additive seasonality predictable over time. This implies that an additive Holt-Winters requires data to have a linear trend with an additive seasonal pattern suiting the PIT time series data.The Additive HW model is presented in Table 1.

Table 1. *PIT additive Holt–Winters model coefficients*

Smoothing Constant	Coefficient
alpha(α)	0.2667
beta (β)	0.0865
gamma (γ)	0.7333
Level Mean (β_0)	9.3401
Growth/Trend (β_1)	0.0305

Source: Authors'computation.

Table 1 represents the smoothing constants, level mean and growth/trend estimation for the additive Holt–Winters model in equation (26) fitted to PIT time series.

$$\ln(y_t) = (9.340 + 0.0305t) + s_t + e_t \tag{26}$$

Equation (26) is the PIT additive Holt–Winters model from Table 1. The estimate mean l_T for the level mean, the estimate b_T for growth/trend rate and the estimate s_T for the seasonal factor of the data in time period T are given by the smoothing equation:

$$\ln(y_t) = (9.340 + 0.0305t) + s_t + e_t \tag{27}$$

$$b_T = 0.0865(l_T - l_{T-1}) + (1 - 0.0865)b_{T-1} \tag{28}$$

$$S_T = 0.7333(y_T - l_T) + (1 - 0.7333)s_{T-1} \tag{29}$$

Where α = 0.168, β = 0.083 and γ = 0.479 are smoothing constants ranging between 0 and 1.The l_{T-1} and b_{T-1} are estimates in time period T − 1 for the level mean and growth rate, respectively, and S_{T-1} is the seasonal factor. More weight is given to the seasonal component of the model, verifying that indeed PIT is a seasonal time series data. The initial seasonal state for this quarterly data was computed as presented in Table 2.

Table 2. Initial values of the seasonal components

S_1	S_2	S_3	S_4
0.005	0.0299	−0.1547	0.1198

Source: Authors'computation.

PIT Holt–Winters model performance and forecast

This section focuses on the Holt–Winters model performance on the in-sample data (training and testing). The model good fit on the sample data enables the model to be used for forecasting purposes with some level of accuracy. Depending on the tolerance level or error range, the model can be regarded as good. The rule of thumb error preference is the 5% error rate; however, other may be comfortable with the maximum error of 10%.

The additive Holt–Winters model fitted on the training data (quarter 1, 1995 to quarter 1, 2014) indicates that the overall standard error was 0.0038, a good fit on the training data. The fitted values in Figure 2 follow or simulate the movement of the observed actual.

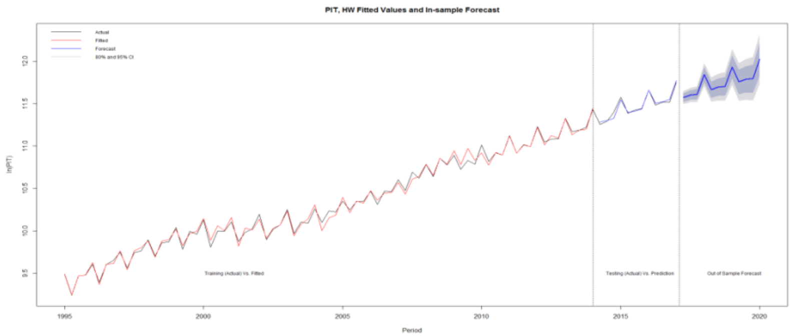


Figure 2. *PIT Actual, Holt–Winters in-sample fitted and forecast*
Source: SARS, & National Treasury (2015, 2016 & 2017) and authors' computation.

The measure of accuracy on the training data is included in Table 3.

Table 3. *Additive Holt–Winters measure of accuracy*

	ME	RMSE	MAE	MPE	MASE
Training	−0.00047	0.03927	0.029054	0.28186	0.28411

Source: Authors' computation.

The additive Holt-Winters model was tested on the sample 2014 and quarter 2, 2014 to quarter 1, 2017. The predicted values follow or capture the movement in the actual values of ln(PIT), as shown in Figure 2. The predicted values were then aggregated to be in line with SARS fiscal year and be compared with the actual for the testing sample period as shown in Table 4.

Table 4. *PIT testing data and additive–HW predicted values in rand millions*

FY	Testing Data	Predicted Values	PE
2014/15	352,950	346,565	1.8%
2015/16	388,101	387,370	0.2%
2016/17	424,545	433,001	−2.0%

Source: SARS, & National Treasury, (2016) and authors' computation.

The percentage error on the three years 2014/15 to 2016/17 (12 quarters) in Table 4 clearly shows the model performance with an error of less than 5% on aggregate which is another indication that this model can be used for forecasting future PIT values.

The model out of sample forecast were generated for the period quarter 2, 2017 to quarter 1, 2020 with the 80% and 95% confidence intervals as shown in Figure 1. Table 5 shows the out of sample three years quarterly forecast.

Table 5. *Cumulative PIT and HW forecast in rand millions*

Quarter	2017/18	2018/19	2019/20
Q01	106,049	116,265	127,465
Q02	215,309	236,050	258,789
Q03	325,510	356,867	391,245
Q04	464,299	509,026	558,062

Source: Authors' computation.

The quarterly forecast amounts to R464,3 billion, R509,0 billion and R558,1 billion for fiscal year 2017/18,2018/19 and 2019/20, respectively. This represents an average growth rate between 9% and 10% for the three years forecast interval. It is a consistent growth rate when compared to the historical growth from 2010/11 fiscal year. The consistence growth due to that PIT is dependent on wages and salaries which normally increase once in a year.

PIT SARIMA model

As discussed in subsection 3.2, in order to fit the SARIMA model the data need to be stationary on the mean with a constant variance. The PIT original series was identified not to be stationary as it changes over time. The normal and seasonal difference was done on the PIT time series presented in section 4. The SARIMA model fitted on PIT using the maximum likelihood method was $SARIMA(0,1,1)(0,1,0)_4$ and can be mathematically represented as follows:

$$w_t = (1-\theta_1 B)\eta_t \tag{30}$$

Where $w_t = (1-B)(1-B^4)y_t$, $y_t = PIT$, θ_1 is the first moving average (MA(1)) coefficient, B is a back shift operator with B is a back shift operator with $B^i(w_t) = w_{t-i}$ and $B^j(\eta_t) = \eta_{t-j}$, and η_t being an error term at time t. However, equation 30 can also be represented as equation 31.

$$y_t = y_{t-1} + y_{t-4} + y_{t-5} + \eta_t + \theta_1\eta_{t-1} \tag{31}$$

Table 6 presents the maximum likelihood parameter estimation for the SARMA model from equation (30) fitted to the transformed PIT time series.

Table 6. *PIT SARIMA model parameter estimated*

	η_{t-1}
θ_1	−0.00047
s.e	0.1263
t-ratio	−3.3512
p-value	0.0008

Source: Authors' computation.

The first moving averages (MA(1) or η_t) fitted on w_t PIT transformed data with the coefficient $\theta_1 = -0.4233$, t-ratio of −3.3512 and the standard error of 0.1263 was found to have a p-value significant at less than 1% level of significance (0.0008).

The SARIMA model fitted will be used to forecast future values if the model residual are white noise. For this reason this study examined the autocorrelation function (ACF) and the partial autocorrelation function (PACF) for a white noise residual as illustrated in Figure 3.

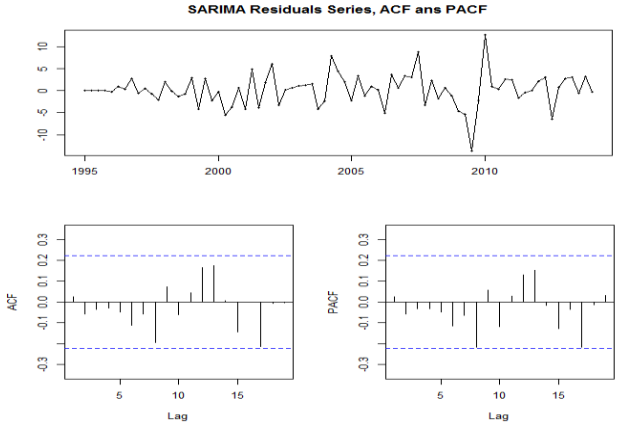


Figure 3. *PIT SARIMA model residuals plot*
Source: Authors'computation.

Figure 3 clearly shows that the model has the residuals which are highly independent from one another. The residuals ACF and PACF SARIMA are within the 95% CI boundaries, where T is the number of series observations. Based on the residual's 95% confidence intervals, the residuals are assumed to be not far from the zero line, that is, they come from a well-defined model. The model, the histogram and the q-q plot in Figure 4 further confirm the independence of the residuals, as the two plots showed the distribution of the residual overtime, with the most of the values centered around zero mean, though there was some skewness.

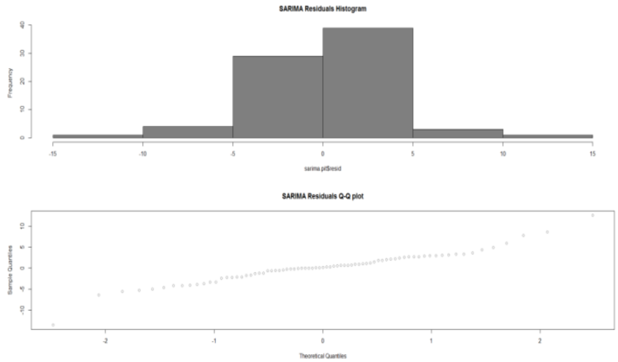


Figure 4. *PIT SARIMA residuals histogram and Q-Q plot*
Source: Authors'computation.

The more general statistics to verify the residual white noise would be the Ljung–Box (LB) test defined by equation 13 in subsection 3.2, which is calculated on the sampled residuals of the model fitted. The Ljung–Box test with a chi-squared of 21.868 from 20 degrees of freedom gave a p-value of 0.3477 was obtained from the SARIMA model. This shows that the residuals are independent or uncorrelated and assumed to be emanating from a well specified model and for this reason the model will be used for forecasting the continuation of the PIT historical patterns.

PIT SARIMA model performance and forecast

This section applied the SARIMA model to analyse the performance of the model training and testing data. Figure 5 present the in-sample fitted values and the model out of sample forecast from the SARIMA fitted model

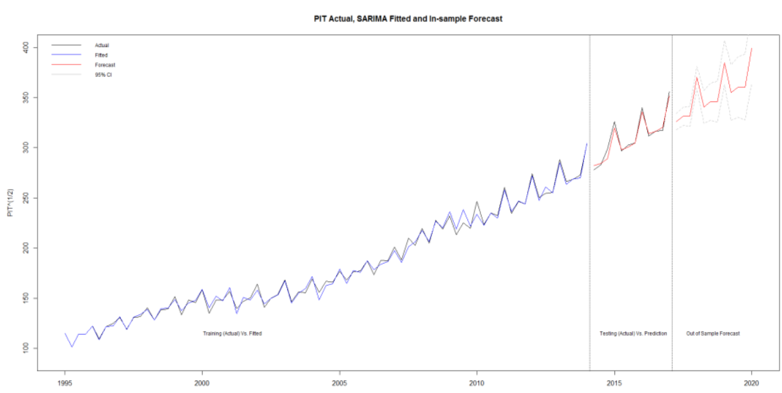


Figure 5. *PIT actual, SARIMA in-sample fitted and forecast*
Source: SARS, & National Treasury (2015, 2016 & 2017) and authors' computation.

The SARIMA model fitted on the training data quarter 1, 1995 to quarter 1, 2014 performed exceptionally well with the fitted values mimicking the actual (Figure 5). The measures of accuracy on the training data are shown in Table 7.

Table 7. *SARIMA measure of accuracy*

	ME	RMSE	MAE	MPE	MASE
Training	164.6617	1505.243	996.2337	0.2616165	2.815479

Source: Authors'computation.

The SARIMA model was tested on the sample 2014 and quarter 2, 2014 to quarter 1, 2017. The predicted values follow or capture the movement in the actual values with minimal error observed as shown in Figure 4. The predicted values were then aggregated to be in line with SARS fiscal year and be compared with the actual for the testing sample period as shown in Table 8.

Table 8. *PIT testing data and SARIMA predicted values in rand millions*

FY	TestingData	PredictedValues	PE
2014/15	352,950	345,890	2.0%
2015/16	388,101	381,850	1.6%
2016/17	424,545	417,809	1.6%

Source: SARS, & National Treasury (2016) and authors' computation

The percentage error on the three years 2014/15 to 2016/17 (12 quarters) are shown in Table 8. It clearly shows the model performance with an error of less than 5%. The models out of sample forecast were generated for the period quarter 2, 2017 to quarter 1, 2020 with the 95% confidence intervals as shown in Figure 5.Table 9 shows the out of sample three years quarterly forecast.

Table 9. *Cumulative PIT and SARIMA forecast in rand millions*

Quarter	2017/18	2018/19	2019/20
Q01	106,561	116,072	125,582
Q02	216,489	235,510	254,532
Q03	326,522	355,055	383,587
Q04	462,588	500,631	538,674

Source: SARS and authors' computation.

The quarterly forecast amounts to R462,7 billion, R500,6 billion and R538,1 billion for fiscal year 2017/18, 2018/19 and 2019/20, respectively. The annual forecasts from the SARIMA model in

Table 9 do not differ much with the Holt-Winters forecast in Table5, signifying that the actual realization will be around the generated forecast.

Time series regression model with SARIMA errors

The regression model with SARIMA error was defined as an expansion of a linear regression model in subsection 4.3. This model relates dependent variable to time and the effect of the explanatory variable(s) included in the model.This study fit the Time Series Regression which relates PIT to Total Compensation of Employees ($Comp_t$). The mathematical representation of this model is shown in equation 34.

$$\nabla^d y_t = \beta_1 \nabla^d Comp_t + e_t \tag{32}$$

$$e_t = (1-B^4)^{-1}(1+\theta_1 B)\eta_t \tag{33}$$

$$\nabla^d y_t = \beta_1 \nabla^d Comp_t + (1-B^4)^{-1}(1+\theta_1 B)\eta_t \tag{34}$$

Where ∇^d is normal differencing of the data, in this case d = 1 and the rest of the notation already defined in the current and previous sections. The $\text{SARIMA}(0,0,1)(0,1,1)_4$ was fitted to the error term in equation 34 which reduces the model error e_t to η_t. The model's parameter estimates, standard error, t- ratio and p-value are shown in Table 10.

Table 10. *TS-regression model parameter estimated*

	θ_1	β_1
Coef	−0.719	0.236
s.e	0.120	0.053
t-ratio	−6.011	4.456
p-value	1.85e-09	8.35e-06

Source: Authors' computation.

The two estimated parameters are significant at less than 1% level of significance. The model will be used for forecasting, thus the study need to examine the normality of the residuals. If the residuals are normal the assumption will be that the fitted values are also normal, hence the model can be used for forecasting purposes. Figure 6 shows the residuals from the model in equation 34.

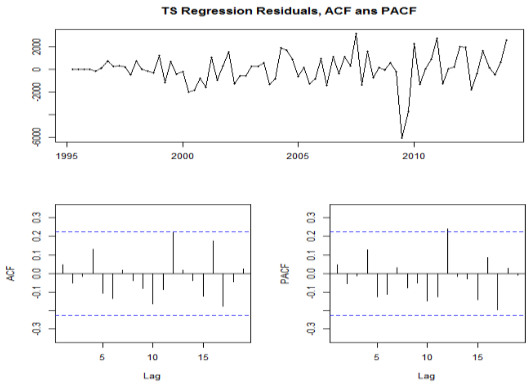


Figure 6. *Residuals from Time Series Regression model*
Source: Authors' computation.

Figure 6 presents the model residuals that are white noise, with their ACF and PACF falling within their 95% confidence interval or boundaries. The p-value of 0.283 was obtained from the Ljung–Box test for normal distributed residuals.The residual white noise was also shown by the histogram and the Q-Q plot in Figure 7.

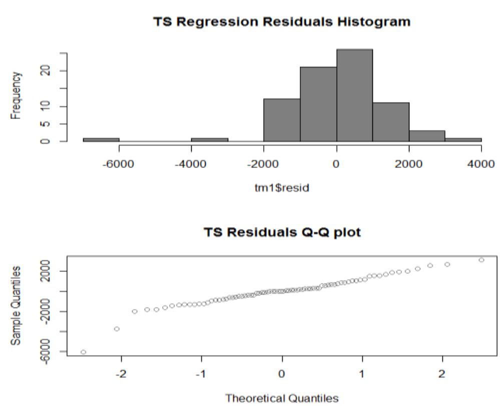


Figure 7. *Residuals histogram and Q-Q plot SARIMA TS-regression*

Source: Authors'computation.

However, to proceed with out of sample forecast for PIT, the explanatory variable forecast need to be obtained first. The $SARIMA(2,1,2)(1,1,1)_4$ was fitted to the square root 1 transformed Compensation of Employees (Comp 2) and the out of sample forecast were generated. The Compensation SARIMA model is represented mathematical in equation 35.

$$w_t = \frac{(1+\theta_1 B+\theta_2 B^2)(1+\Theta B^s)}{(1-\phi_1 B-\phi_2 B^2)(1-\Phi B^s)}\varepsilon_t \tag{35}$$

Where d and D are normal and seasonal differencing respectively, s = 4 for quarterly data used, thus $w_t = \nabla^d \nabla_s^D Comp_t^{\frac{1}{2}} = (1-B)(1-B^4)Comp_t^{\frac{1}{2}}$ and ε_t is the error term at time t. The model's parameter estimates, standard error, t-ratio and p-values are shown in Table 11.

Table11. *TS-regressionmodel parameters estimated*

	ϕ_1	ϕ_2	θ_1	θ_2	Φ_1	Θ_2
Coef	1.538	−0.863	− 1.608	0.780	− 0.676	0.834
s.e	0.092	0.073	0.133	0.128	0.193	0.148
t-ratio	16.760	− 11.872	− 12.115	6.093	− 3.506	5.651
p-value	4.82e-63	1.66e-32	8.83e-34	1.11e-09	4.55e-04	1.59e-08

Source: Authors'computation.

The estimated parameters are significant at less than 1% level of significance. The model will be used for forecasting. Subsection 4.6 presents the Time Series Regression with SARIMA error performance on the in-sample data and also shows the out of sample forecast.

Time series regression model performance and forecast

The Time Series Regression with SARIMA errors built on the PIT training data quarter 1, 1995 to quarter 1, 2014 derived the fitted values that follows the actual realisation of PIT (Figure 6).

The measure of determination R^2 was computed to be around 0.883 for the model fitted; this implies that 88% of the variation on the transformed PIT was explained by this model. Some measures of accuracy on the training data set are shown in Table 12.

Table 12. *Measure of accuracy from time series regression*

	ME	RMSE	MAE	MPE	MASE	MASE
Training	0.0238	1375.01	962.7847	10.8045	59.6951	0.8088

Source: Authors'computation.

Moving out of the training data sample the model was tested on the sample 2014 and quarter 2, 2014 to quarter 1, 2017. The predicted values were then aggregated to form SARS fiscal years forecast and were compared with the actual for the testing sample period as shown in Table 13.

Table 13. *PIT testing data and TS-regression predicted values in rand millions*

FY	Testingdata	Predictedvalues	Percentage Error
2014/15	352,950	343,200	2.8%
2015/16	388,101	374,672	3.5%
2016/17	424,545	407,153	4.1%

Source: SARS, & National Treasury (2016) and authors' computation.

The percentage error on the three years 2014/15to 2016/17or 12 quarters in Table 13 clearly show the model performing with an error of less than 5% though the error was leaning to wards5% error as compared to the other methods above. The models out of sample forecast were generated for the period quarter 2, 2017 to quarter 1, 2020 with the 95% confidence intervals as shown in Figure 6. Table 14 shows the out of sample three years quarterly forecast.

Table 14. *Cumulative PIT actual and TS-regression forecast in rand millions*

Quarter	2017/18	2018/19	2019/20
Q01	93,604	102,635	111,924
Q02	190,869	209,127	227,588
Q03	288,580	316,347	343,910
Q04	412,067	449,262	485,476

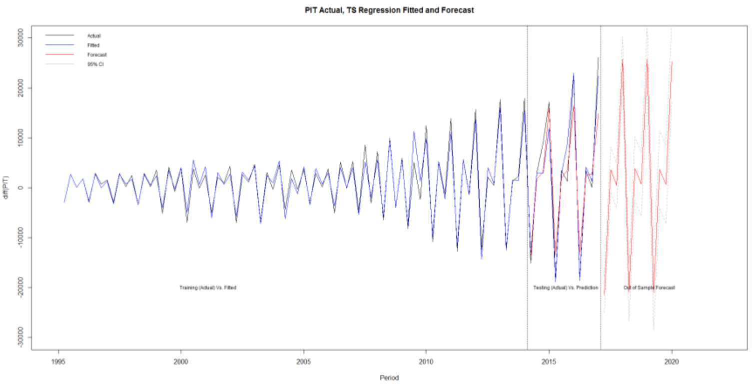


Figure 8. *PIT actual, TS-regression in-sample fitted and forecast*
Source: SARS, & National Treasury (2015, 2016 & 2017) and authors' computation.

The quarterly forecast amounts to R412,1 billion, R449,3 billion and R485,5 billion for fiscal year 2017/18, 2018/19 and 2019/20, respectively. The annual forecast from the TS regression model are little bit lower than Holt–Winters and SARIMA forecast in Tables 5 and 9, respectively. Figure 8 presents the in-sample fitted values and the model out of sample forecast from the SARIMA fitted model.

Discussion of results and limitations

Accurate fore casting of these taxes could further assist with predicting future collections, as well as detecting false reporting of information by individuals. However, in any economy there will always be some form of tax evasion and avoidance from individuals, which could be a result of a lack of tax knowledge and/or system manipulation.

This chapter presented the modelling of the South African personal income tax in rand millions using the time series models Holt–Winters, SARIMA and Time Series Regression with SARIMA errors. The ultimate task was to introduce and to show the power of prediction when using these models if predicting the fiscal years outcomes. Though every model has its own advantages and disadvantages, the time series are seen as the base of forecasting (preferably for short term).

The SARIMA and HW model assumes all the explanatory variables are incorporated in the historical movements or patterns hence the TS regression with SARIMA Errors allows the inclusion of the explanatory variable(s) and SARIMA model for the un-explained portion of the dependent variable. However, there are other methods which can also be exploited for forecasting such as the GARCH model, the VAR models and so forth.

Table 8 compares the forecast from the three methods for the three years (2017/18, 2018/19 and 2019/20) with PIT as a variable of interest and the average (AVG) forecast from those models.

Table 8. *Forecast comparisons in rand millions*

FY	FY	Holt–Winters	SARIMA	TS-Regression	AVG Forecast
2017/18	2014/15	464 299	462 588	412 067	446 318
2018/19	2015/16	509 026	500 631	449 262	486 307
2019/20	2016/17	558 062	538 674	485 476	527 404

Source: Authors'computation.

The results for the PIT forecast from the Holt–Winters and SARIMA model converges and the TS-regression forecast are a bit lower than the forecast from the two models. This also confirms the assumption that pure time series are the bases for forecasting. The location of the actual realisation is assumed to be around the forecast from the three models with some acceptance error margin; hence the average forecast could be used.

As indicated earlier, these methods are good for short term forecast (i.e. three to five years forecast) as they lose prediction power when forecast period stretch forward. The effect of structural shock and other unknown phenomenon could results in a model forecast that are far away from the actual, therefore careful follow up of these models is recommended. The good forecasting practice will be to monitor the actual realisation as it shows up andrevise the forecastif necessary.

Conclusions and recommendations

The Holt–Winters model, SARIMA model and Time Series Regression with SARIMA error were used to model and forecast personal income tax for the South African economy from which it was observed that the models captured the movement of these taxes with higher precision on the in-sample data used. This is shown by the computed in-sample measure of accuracy such as Mean Error (ME), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Percentage Error (PE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE), Mean Absolute Squared Error (MASE), Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) on the training sample data spanning quarter 1, 1995 to quarter 1, 2014.

The sample data from quarter 2, 2014 to the quarter 1, 2017 were used to test the model strength by comparing the predicted values to the actual PIT collection for the same period. Using the sample with recent actual PIT collection up to quarter 1, 2017, the out of sample forecasts for the period quarter 2, 2017 to quarter 1, 2020 were generated from the fitted models. The quarterly forecast was then aggregated to form SARS fiscal year forecast (SARS fiscal year span from April to March).

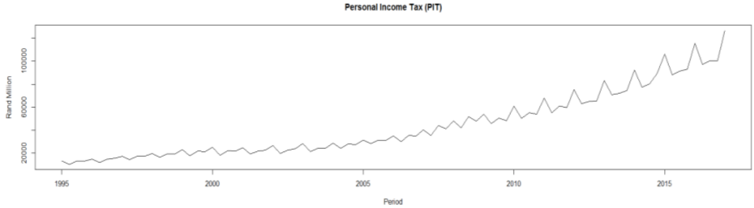
The study recommends the use of these models when forecasting future PIT payments, because they are precise and unbiased in forecasting tax revenue with minimal error for short term, preferably the Holt–Winters and SARIMA models. The results of this study will assist the South African authorities with decision making for future revenue management, resources allocations and distribution of revenue collected to the government departments with accuracy. These types of models could also be used as back up or for a measure of correctness of the economic models, as they do not introduce bias when predictions are done.

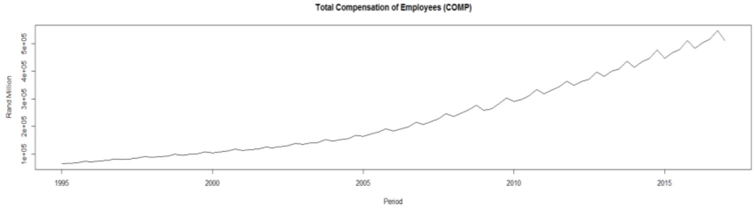
The techniques portrayed in this paper are properly documented for the development of other models to be used for various purposes. Scope for further research on analysing the Value Added Tax (VAT), Corporate Income Tax (CIT) and Total tax revenue will depend greatly on techniques used in this study.

Appendix

Appendix 1

PIT actual and total compensation of employees (COMP)



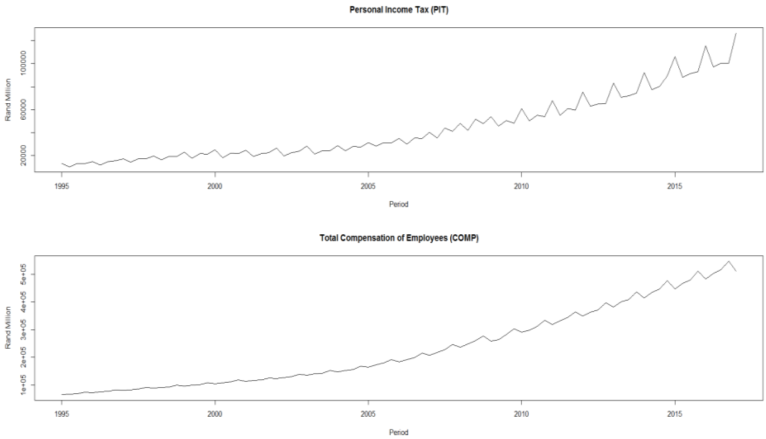


Source: SARS & National Treasury (2015, 2016 & 2017) and Statistics South Africa (STATS SA).

Notes: Appendix is the South African quarterly actual PIT data and total compensation of employees (COMP) for the period Quarter 1, 1995 to Quarter 1, 2017.

Appendix 2

PIT actual and total compensation of employees (COMP)



Source: SARS & National Treasury (2015, 2016 & 2017) and Statistics South Africa (STATS SA).

Notes: Appendix is the South African quarterly actual PIT data and total compensation of employees (COMP) for the period Quarter 1, 1995 to Quarter 1, 2017.

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4 Agrarian system dynamics and traits on the western slopes of the Manengouba Mountain

Nkumbesone Makoley **Essone** [a †]
Etamesone **Diabe** [b]
Ejuande Emmanuel **Wonomu** [c]

Introduction

The recent population change in Cameroon has had significant effects in the population size in both the urban and the rural areas and in the agricultural sector in particular. Agricultural dynamics occurring in many rural areas is partly accounted for by the technological advancement and the change of farming behavior by the locals. The FOA looks agriculture as the cultivation of crops and rearing animals. Agriculture has remained the oldest activity of the world's population today and it stood as the cornerstone of the upsurge of most economies in the world (Fogwe, 2016; Ba'ana, 2017).

[a†] Société Savante Cheikh Anta Diop (SS-CAD), Faculty of Letters and Social Sciences, University of Douala-Cameroon.
☎. (+237) 696 363 221 / 675 801 284 ✉. etamesonediabe@yahoo.com
[b] Société Savante Cheikh Anta Diop (SS-CAD), Faculty of Letters and Social Sciences, University of Douala-Cameroon.
☎. +22890113949 ✉. kouevidjin54@gmail.com
[c] Société Savante Cheikh Anta Diop (SS-CAD), Faculty of Letters and Social Sciences, University of Douala-Cameroon.
☎. (+237) 675 801 284 ✉. emmanuelfrancis@yahoo.fr

The developed countries have a more efficient system of agriculture where a few people supply food for whole of the nation, while the developing countries present inefficient system of agriculture which is furnished with low productivity where farm laborers barely sustain farm population. These two agrarian systems reveal the existence of an immense gap between them. In I960 for example, 115 million people in the developed countries were engaged in the agricultural sector and they produced a total yield of $78 billion, hence per capita agricultural production was of $680. Conversely, in the developing countries a bunch of 850 million people were engaged in the agricultural sector and they produced agricultural output worth $43 billion and hence per capita agricultural production was merely $52. This shows that there existed a gap of 13 times in labor agricultural productivity in developed and the developing countries. In 1980, 96 million people in the developed countries were employed in agricultural sector, producing a total worth $125 billion and per capita agricultural production was $1660. On the contrary, 1230 million people in the developing countries were engaged in agriculture, realizing a total worth $77 billion and the per capita agricultural production was $63. These few examples show that the productivity gap in agricultural sector between the developed countries and the developing countries is widening day by day.

In the context of Cameroon, the activity employs close to 70% of the active population and contributes greatly to foreign exchange earning to more than 40% GDP. Agriculture is the main economic activity undertaken by the population of the Manengouba Mountain on the Bakossi highlands wherein about 92% of the active population is engaged in the agricultural practices. Over 75% of the farmers are small scale holders and the extensive subsistence method of farming is widely practiced.

Research methodology and data analysis

Presentation of the study area

The study area the Manengouba is a Cameroon village situated in the South West region, the Bakossi highlands stretch between latitudes 4° 51' N to 5°72'N and longitudes 9° 37'E to 9° 58'E. This region is characterized by a number of peaks; the Manengouba mountain 2 412m, the Eboga peak 2 078m with an escarpment that runs from Mbouroukou, Muenengel, Poala, Muabi Mbat, Nkikoh to Nyan. A steep slope also runs on the other side through the following villages; Mueba, *et al.*, (2007) noted that from Ekambeng through Bangem to Ndibse and Enyandong is gentle sloping and dissected with average heights of 1 200m in Muadelegoe inselberg. Nteho and Ekanjoh-Elung are considered as the trough as they are just 450-621m and Ebamut at 1 900m altitude. Put together, these dynamisms of relief features constitute the essence of the Manengouba Mountain. Moreover, this locality is the watershed from whence some streams take their rise. Among them are: the Chide, Chunge, Mekunge, Mbwe, Mbe and the twin lakes. The vegetation covers equally presents attractive features like the grass vegetation on the highs top and the forest vegetation in the valleys. The study zone is represented in the figure 1.

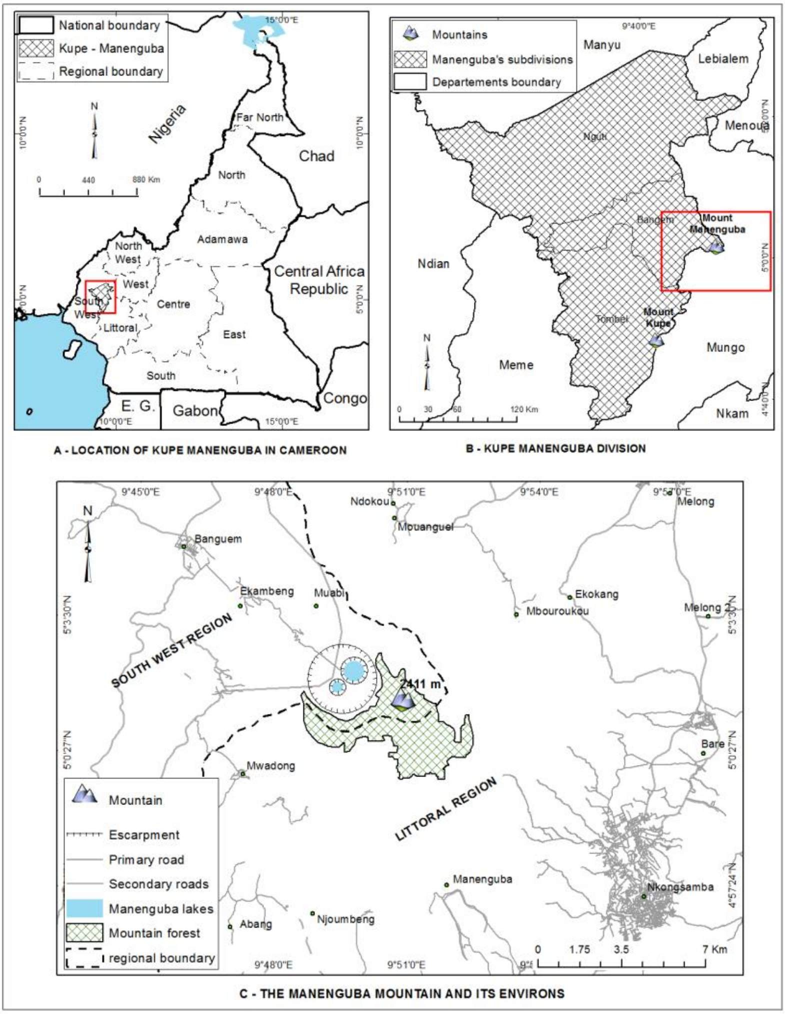


Figure 1. *Location of the study area*
Source: Nkumbesone *et al,* 2019.

The study area is at the frontier of two administrative regions and Divisions, part of the inhabitants are English speaking while the other part is French speaking. The presence of lakes and mountains beautify the geographical terrain of the area and set the pace for agrarian system of farming to drive well.

Data collection

The methodology used in this paper is the geographic method of investigation that comprises of four stages: Observation, Description, Analysis and Interpretation of facts and phenomena in the society. It also privileged the pluri-disciplinary approach of research that analysis the relation between the local population and their environment. Data on the agrarian system of farming on the study area were collected through the geographic method of investigation and the pluri-disciplinary approach.

Qualitative data were collected through observation (*in situ* observation and participating observation) and interview (direct and indirect interview) with mature individuals and households who have been carrying out the farming activity for not less than 07years. On the other hand, quantitative data were collected through survey. These data were gotten from the following sources; the sub-divisional delegation for agriculture and rural development in Bangem, the sub-divisional delegation of fisheries and animal husbandry in Bangem, the archives of the Bangem rural council and the archives of the Bangem Co-operative Credit Union Ltd, etc… The survey was done with a total of 250 questionnaires administered in respect to some geographic, socio-economic, socio-cultural and socio-political criteria of the territory such as: center-periphery, demographic composition and social amenities.

Data analysis

The study used two types of questions in the questionnaires and two types of data. The first set of questions were fixed choice questions in which the informant had to choose an item amid several modalities, it is equally in the form of “Yes” or “No” questions. On the other hand, the questionnaires had open-ended questions which permitted the informants to give their views freely on the agrarian types and practices. This exercise saw the codification of responses from both questions types and later expressed as percentage for a better interpretation. Secondly, the qualitative data were analyzed with the help of MACTOR software to evaluate the various roles of the stakeholders within the framework of this study; it equally helps to analyze the socio-cultural behaviors of the farmers to the farming types; while quantitative data were treated with the help of SPSS, Excel 2007 and QGIS, Philcarto and Phildigit.

These processes have helped in establishing the interrelation between the stakeholders; SPSS 21.0 has permitted to analyze socio-demographic, Excel 2007 has permitted to further analyze data from SPSS and draw appropriate illustrative graphs. QGIS, Philcarto and Phildigit were used to locate the study area which ended with the production of a location map of the study area.

Results and discussion

Mountain colonization

The colonization of the environment by the human population in Cameroon dates back from the early history of the earliest inhabitants of Cameroon. History points out that the Baka (Pygmies) were probably the first group of occupants who still inhabit the forest zones of the south. Historians advocated that the Bantu people originated from Cameroonian highlands areas before the coming of other invaders. During the 1500, the Mandara Mountain was solicited and later other mountains peaks in the North West, West, and the South West became interesting sites to the earliest occupants. These mountain peaks were mostly solicited for some of the following reasons:

War purposes; majority of the inhabitants in the ancient time were more barbaric and war lovers than this present generation of occupants. Mountain peaks, hills and plateau served as natural strategic defensive and offensive sites against the invading enemies. The high altitudes areas permitted the inhabitants to easily notice the coming of their enemies; this gave them time to alert the group for attack. Sporadic attacks from invading enemies were frequent at the time since each group wanted to have dominion over other groups. The presence of wild animals; the population density by this time was low and the demographic growth was equally low, people live in closed contact in fear of wild animals and harmful insects in the valleys and plains. In the early 19th century, the Fulani people who were Islamic pastoral group from the western Sahel conquered a large part of the northern Cameroon and later subjugated its majority non-Muslim inhabitants.

The population rapidly spread across the country with the occupation of both mountainous areas and plains. In the South West region of Cameroon and precisely in the Manengouba, the colonization of mountainous areas only became increasingly intensified after the outbreak of the economic crisis of the late 80s, this contrast with the situation of the Mandara mountain area and in the western Sahelian zones. Before the 80s, the occupation of these mountainous areas was not remarkable not until the economic crisis hited the economy, igniting the desire to search for possible alternative measures by the different stakeholders to subdue the crisis. The figure before presents the location site of the study area.

The figure1 shows the global view of the western slopes of the Manengouba Mountain on the Bakossi highlands with specific realities of human occupation. It should be noted here that the occupation and transformation of the natural vegetation into the agrarian system of agriculture started increasing as from the early 90s where the local population seeks ways to exploit the natural resources of the environment for their socio-economic and socio-cultural welfare. The primary forest areas of Muanjikom and Enyandong and the secondary forest areas of Muambond, Bangem and Eloum were progressively colonized. Most of these forest areas have been considerably decreasing as human activities keep intensifying on the areas. The savanna zones and the mountain forest zones are greatly affected by human encroachment and pastoral activities taking place in the area.

Socio-cultural composition of the area

The Manengouba area is about 80% occupy by the local indigenes who are the Bakossi people, about 20% of the occupants have other origins, all of which is represented in the figure 2 below.

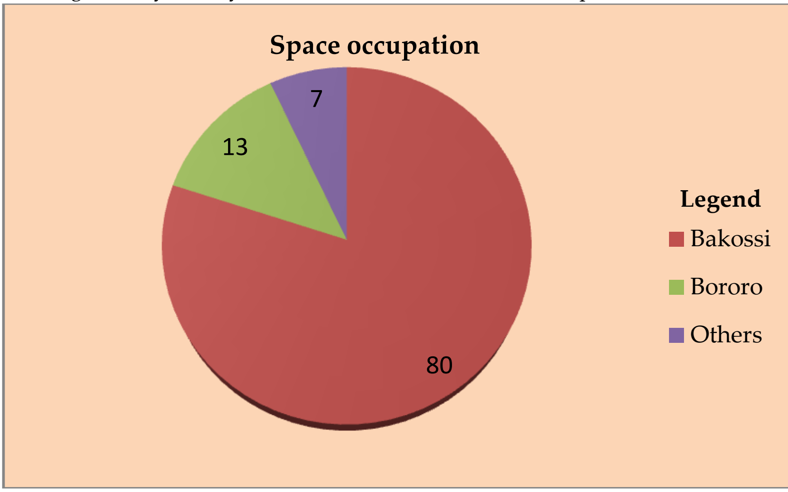


Figure 2. *Space occupation in the Manengouba area*
Source: Field work 2019.

The figure 2 represents the different percentages of occupation by the various stakeholders in the field of study in 2019. The autochthones who are the Bakossi people represents up to 80% and mostly occupy the low-lying areas while the Bororo people who represent about 13% mostly reside on the mountains top. The 7% represents people from the grass-fields (North West region and the West region), the Mbo and people from other parts of the South West region. Initially, before the 80s the western slopes of the Manengouba Mountain had it natural green vegetation full of variety of plants and animal species, the rich natural nature became a point of attraction to farmers and herders who constantly seek to dominate the nature in order to satisfy their desires.

The population is made up of about 99% people of the English expression or the Anglophones who have a unique lifestyle and socio-cultural practices that are identical to each other. The cultural practices were initiated long ago before the coming of the British into Southern Cameroon. The arrival of the colonial master (the British) only fostered the already existing system of functioning of the English speaking Cameroonians who had well established cultural system led by the chiefs in each local community. The local populations of the Manengouba Mountain have constituted themselves into ethnic groups headed by chiefs; they live in grouped/compacted settlement and share moments of joy and sorrow as a family.

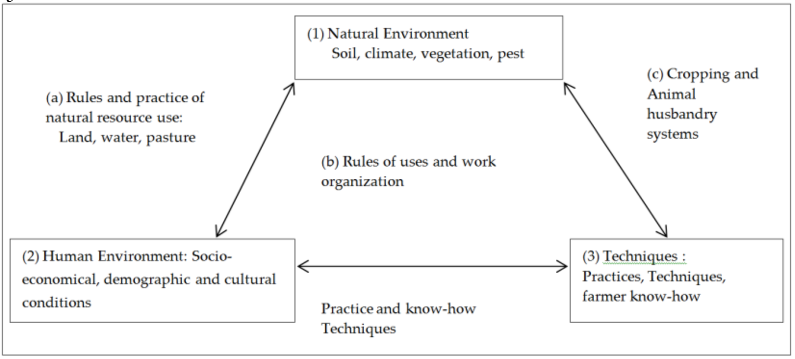
Anthropic activities

Identification of the agrarian system of agriculture in the study area

The agrarian system of agriculture is one in which the farmers exploit the environment by using the relations and interactions that occur between all of its social and physical components. It also considers the limits of the environment and its ability to reproduce. Derruau (1960) defined the "agrarian system" as "the spatial arrangement (plot layout, fences and boundaries) and the temporal organization (crop rotations, permanent crops) and their relationship with techniques and social factors (community practices, land ownership patterns). Moindrot (1995) considered the concept to include the study of agrarian "landscapes", farming systems, and land ownership. However, these definitions raise the problem of scale. This has made some geographers to proposed typologies for the different farming systems and Marcel Mazoyer in 1970s and 1980s reappraised the concept of the agrarian system, this led to the combination of the mode of exploitation of an ecosystem. That is, it is seen as an "agro-system" -, the technical system, and the socio-economic logic governing the whole system.

According to Nafri *et al.*, (2005) the agrarian systems approach takes a historic perspective by taking into account the spatial and temporal limits of an agrarian system. The system tries to understand the organization, the operation, the renewal and the differentiation of the past. The aim here is to provide a better understanding of the complexity of the present dynamics, the socio-economic structures and the mode of exploitation of the ecosystem. The agrarian system in the Manengouba Mountain is composed of three main components as presented in the table1 below:

Table 1. *Reciprocal relationships between components of an agrarian system*



Source: NAFRI *& al*, 2005

The Table 1 presents the reciprocal relation between the three main components of an agrarian system with the natural environment representing the first component, human environment and techniques representing the second and third components respectively. The natural environment is the platform on which all human activities take place; it can influence human activities through temperatures, precipitations, vegetation, etc and vice versa. The human environment through socio-economic and demographic conditions of the population of Manengouba has a great influence on the agrarian system of the area. The farming system, the practices and the techniques of the locals play a great role in determining the yields in each farming unit.

Typology of the agrarian system identified

The Manengouba area has a varied agrarian system, some of the systems identified on the field include: shifting cultivation/bush fallowing, extensive subsistence farming and the grazing of animals.

Shifting cultivation/ bush fallowing

In its simplest form of reasoning the concept shifting cultivation refers to displacing of both land and settlement, it is also a farming system by which the land under cultivation is periodically shifted so that fields that were previously cropped are now left fallow.

Filed investigations reveal that only the farm lands are being shifted while settlement remains as a result of increase literacy in the Manengouba area. The farming methods used by the local population are mainly slash and burn, crop rotation and crop fallowing. The farmers rely most on the atmospheric conditions before engaging into any planting of crops. Seeds are selected, planting material get ready; the farmlands on the mountain areas are cleared and burnt during the dry season in anticipation for the early rains to begin planting. During this time the herders move with their cattle down the hills in search of pastors because most parts the hills top have been deprived of their natural vegetation by human encroachment. Planting begins with the early rains of March which marks the start of planting season in most parts of Cameroon. As the rains continue to their peak in the month of august, the herders make a 'U-turn' with their cattle back to the mountain tops where there is now enough pastors for the cattle; this situation is called transhumant. One of the particularities of the agrarian farming system observed in this study zone is that there exists an inverse domination of sex in each farming system; the pastoral farming system has a masculine domination led by the Bororo while the other agricultural types are largely dominated by the feminine population of the Manengouba. The women account for about 75% against 25% for the men while in the pastoral system, the men account for about 95% of the herders. This contrast in the participation of both sexes into the farming system is also partly explained by the cultural background of each ethnic group.

The women usually constitute themselves into groups or what is commonly called '*Njangi group'* this group has as main objective to give mutual help to each of the member who faces challenge in her farm. They usually move from one member's farm to the other to clear, burn, plant or to harvest depending on the set objective of the day. In this shifting cultivation system, a farm plot of about 8hestares can be repartitioned into four separate plots representing 02 hectares/plot to be farmed for four years. The farmer would then be shifting from one plot to the other as the years unfold.

Bush fallowing

The practice of bush fallowing on the western slopes of the Manengouba Mountain on the Bakossi highlands reveals to be an improved shifting cultivation system in which farmers cultivate on a particular piece of land for one, two and even for three years before abandoning the site to a new site. The reason behind such a rotational type of farming is to permit the cultivable surface area to regain its fertility and be productive. The system as observed today shows great contrast with the hitherto practice which was more of rotating the cultivable land area than the crops, but today both the cultivable lands and the crops rotate due to improve agricultural technologies, literacy rate and increase in the prices of goods and services at the local markets as well as in the international market. The Table 2 represents the fallowing of some common crops cultivated in the study area.

Table 2. *The fallowing of some common crops in the study area*

Crop types	Rotation schedule	Type of rotation (land and crop)	Type of cropping system
Beans	2 years	Both	Mixed and relay intercropping
Cassava	1 year	Both	Mixed and relay intercropping
Coco-yams	2 years	Land	Strip, relay, mixed and row intercropping
Maize	2 years	Both	Mixed intercropping
Plantain	3 years	Both	Row, strip, relay and mixed intercropping

Source. Field work, Nkumbesone 2019.

The Table 2 presents the fallowing system of some main crops cultivated on the farmlands within the Manengouba area. The fallowing of some crops like coco-yams, maize, cassava, etc… around the forest areas of Enyandong is mainly to allow the cultivated plot to regain its natural fertility over a period of one to two years depending on the crop type and on the yield per surface area. Cassava is one of the rare crops that the local farmers hardly repeat on the same piece of land. They explained cassava produce very low yields when repeated unlike plantain which can be rotated upon after three years or maize after two years. The table equally shows that most of the crops are rotated upon on both sides (land and crop). Mixed cropping system is dominant where the farmers do plant other crops on the same plot harboring the main crop.

Compound farming

This farming system can also be called 'home based farming' and it is practiced 95% by the women population on the western slopes of the Manengouba Mountain on the Bakossi highlands. In fact, this farming system which equally represents some sort of gardens around settlement areas is characterized by small plot sizes of 05m^2 to 100m^2, the women plant highly perishable crops of market gardening type like vegetables, pepper, *water-leave*, okra, some fruits (garden egg) and on the other hand they plant plantain. In the Bakossi highlands area, the women equally grow snail which is part of their staple food in the area, the backyards are good sides for the practice. The practice is becoming very recurrent due to the nutritional and economic values of the snails. In other interior villages of Mbang, Elah, Chukte and Muanjikom, tree crops surround the village setting.

Intensive subsistence farming

These are small scale farms on which vegetables like cabbages, tomatoes, carrots, pepper and lettuces are grown. This farming system came to light in the early 90s on the western slopes of the Manengouba Mountain on the Bakossi highlands where youths constituted themselves into groups and associations known as '*Chomencam youth*'. By the time, the association total to 90 members with only 14 females, but as time unfolds; the young men progressively dissociate from the association and were replaced mainly by the female folk. The female population has been till present the main backbone of the local development ongoing though little consideration of the vital rule they play is given to them (Ejuande, 2017). Soon after, the cultivation of pepper became dominant in the localities of Ngonmin, Muambong and Ndibsi. The intensive farming is widely spread in swampy areas around Mbat and also on the highlands where ridges are made to counterattack the effects of runoff from the hill tops to the plains. On the highland areas, a terracing form of cultivation is common.

Intensive cultivation is also practiced around the baby lakes on the floor of the Eboga caldera on the Manengouba Mountain. Around the Ndibsi, the long stemmed colo cassia is planted by stream sides where the currents are a beat reduced. The young sets are held steadfast in the stream by stones which support them from being swept by the running waters. This colo cassia rich in iodine is usually harvested and early consumed by the households or sold in the neighboring local markets of Bangem.

Extensive farming system

Extensive farming system within the perimeters of the Bakossi highlands is dominantly practiced with cash crops like cocoa, coffee and rubber. Other food crops are equally practiced on an extensive manner. This study identifies two types of extensive farming in the study area which are Extensive subsistence farming and Extensive commercial farming.

Extensive subsistence farming

Just as the name implies, this farming practice is basically for home consumption. The farmers cultivate on relatively large plots of lands which vary from 1 hectare to 10 hectares of land, there is less use of chemical fertilizers and modern farming equipment, high use of man-power and general low yields per head and per hectare. The food crops cultivated here are maize, coco-yams, plantain, beans and cassava. This farming system usually suffers from the effect of erosion when situated on hilly areas (Mbifung-Lambi, & Ndenecho- Neba, 2009).

Extensive commercial farming

The extensive commercial farming system is on the rise on the western slopes of the Manengouba Mountain on the Bakossi highlands due to the increase in the general prices of goods and services in the economy and due to the level of literacy in the area. The farming system is mostly carried out by those who are economically viable or those who can afford to have at least 300 000 FCFA to solely invest in the farming sector; the money serve to cover some charges like: renting of hectares of lands (1 hectare= 50

000 fcfa/year, 3 hectares = 150 000 fcfa/year), clearing (1 hectare = 30 000 fcfa), purchase of seeds for a hectare and transportation to the plot (15 000 – 50 000 fcfa/ hectare), planting (10 000 – 30 000 fcfa/ hectare) and harvesting (10 000 – 30 000 fcfa/ hectare) all depending on the type of crop. So mathematically, farmers engaging into the extensive commercial farming budget themselves to spend not less than 300 000 fcfa in a planting season in order to obtain high outputs at the end of the planting season; those who can not afford to have such an amount prefer to join farmers association where they can easily obtain assistance.

The extensive commercial farming as observed in this field of study is not only limited to the planting of a single crop on a piece of land, it is equally a mixture of crops of varied duration of maturity. The cassava which takes relatively longer period of time (1year) before attaining maturity is simultaneously planted with groundnut which barely takes three months to get mature. Cocoa is simultaneously planted with plantain. The vertical and horizontal pattern of crops equally determines whether or not the crop should be alternately planted with another, example here is maize and groundnut, maize and beans, maize and potatoes, etc.

Effects of the farming system on the population and the environment

The cultivation of different types of food and cash crops on the Manengouba Mountain on the Bakossi highland has remarkable consequences on the local population and on the environment. Though the increase in the outputs of some crops like maize, cassava, plantain, etc resulting from increase use of chemical fertilizers has been recorded in recent years, the positive effects do not undermine the negative side of the practices. It is true that the agrarian farming in this study area has improved the welfare of the locals, children have been able to pursue their education with revenues from the farming activities, increase protein intake from snail farming and consumption in over 90% of households and enhancement of local development in the area like the rehabilitation of road network from community initiative, financing the educational sector and the building of local churches (Banque Mondiale, 2008; Bella, 2009; Modika, 2016).

The negative effects of the agricultural practices are a call for concern which requires immediate actions to mitigate the impending huge dangers. Some of the youths who make their way into the economic sector either through the umbrella of giving assistance to their parents or their relatives or by operation seasonally to raise money for the next academic year, end up by being charmed by the love of money. The abrupt end of their educational career without getting to the zenith of education and enjoy the beauty of the sapiens places the society at risk of nurturing ignorant generation capable of crumbling a prepared nation for emergence by the predecessors of the nation. It is also applauded that the local populations are engaging into the use of chemical fertilizers to boost agricultural production per hectare, but the level of literacy rate does not equate the type of chemical fertilizers used. For every 10 farmers investigated, 06 do not have a good mastery of the chemical fertilizers they use, talk less of mastery the methods of application. 02 out 05 farmers receive information on the use of chemical fertilizers from a third party either through oral presentation or by sight.

More so, the various equipment use in farming and the method of farming represent further threats to the environment. The local populations make use of hoes, cutlasses, sticks, wheelbarrow and trucks. The cutlasses and sticks are mostly used by the men to clear the farms ready for planting with the hoes by the women. In the case of potatoes, ridges are prepared using hoes while the cocoa-yams require the tilling of soil to burry the seeds and allow them to germinate. Since most of the farming is done on the hilly areas, it automatically requires special farming methods to be used (Morin, 1988; 1989). However, this is not the case; they farmers go about mounting ridges without the least consideration of the effects of erosion on their crops. Some of the ridges are mounted parallel to the hills; the soils are over-tilled thereby exposing the soils to water erosion during the rainy seasons. The fact that the soils are over-tilled, they further suffer from leaching which makes them become less fertile in the course of time. The continual removal of the 'O' horizon which equally has lots of humus leads to environmental degradation and drop in the total outputs per hectares observed this recent times within the field of study.

Conclusion

This chapter presents the agrarian system dynamics on the western slopes of the Manengouba Mountain on the Bakossi highlands from its different forms of cultivation of crops and animal rearing, types of crops cultivated and surface area occupied by each stakeholder. It went forth to presenting the advantages of the agrarian system of agriculture to the local populations and their community. It finally ends up by presenting the negative effects of the agricultural practices to the populations and on the environment (environmental degradation).

This paper recommends that farming system on the Bakossi highlands be done by mounting ridges horizontally to the hills rather than vertical placement. This is in a beat to reduce the effects of water erosion already observed on the study area. Secondly, crops types should be alternated and favor more of creeping crops like potatoes and beans as well as groundnut which all have a good gripe at the soil limiting surface erosion. The training of the farmers is inevitable, the government and other stakeholders like the international partners and the civil society should organize regular training sessions to update farmers on new productive method which is less time consuming and of low cost (Melachio, 2016; Mendras, 1967). Finally, the community participation through association or groups should be reinforced.

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5 Modelling the shadow economy of South Africa: Using the currency demand and MIMIC approach

Mangalani P. **Makananisa** [a†]
Cathrine T. **Koloane** [b]
Friedrich **Schneider** [c]

Introduction

South Africa is the second largest economy in Africa, second to Nigeria. Among the key sectors that keep the economy running are the manufacturing, wholesale and retail trade, financial services, transport, mining, agriculture and tourism. The economy is however dominated by finance and business services (19%), government (18%), trade (15%) and manufacturing (13%). The South African economic growth has been stagnant in recent years and the current load shedding has aggravated the situation

[†a] South African Revenue Service, Operational Research, Pretoria, South Africa.
☎. +2782 4564669 ✉. manginduvho@gmail.com
[b] South African Revenue Service, Operational Research, Pretoria, South Africa.
☎. +2782 906 0090 ✉. Tkoloane09@gmail.com
[c] Johannes Kepler University Linz, Research Institute for Banking & Finance, Linz, Austria.
☎. +43 732 2468 7340 ✉. Friederich.schneider@jku.at

with no real growth prospects expected in the future. The International Monetary Fund (IMF) has cut South Africa's growth prospects for 2020, expecting only a measly 0.8% growth rate (Business Tech, 2020).

Traditionally, South Africa's economy has been mainly dependent on the primary sector and mining was a key output, particularly gold mining. Mining has been the foundation and the driving force behind South Africa's economic and industrial development that carried South Africa onto the world stage. However, over the past 15 years, the overall mining production has declined marginally mainly due to the decline in gold production (SA Mine, 2019). Since the early 1990s, South Africa has seen a structural shift in output with the tertiary sector, which includes wholesale and retail trade, tourism and communications, now taking centre stage (Brand South Africa, 2018).

According to the Mineral Council South Africa (2020), illegal mining is on the rise in South Africa. It is now taking place on a large scale nationally. Furthermore, the UNCTAD report (2016) refers to fraudulent misinvoicing of precious metals by traders in order to evade and avoid payment of taxes.

South Africa is used as a strategic gateway to Europe by most African countries. Its great infrastructure and accessible modes of transport has made it even more attractive for foreign investments. As a result, South Africa has seen an influx of foreigners establishing businesses in the country. Some of these foreigners are en- route to Europe and whilst in the country establish small businesses such as retail shops, salons, internet cafes and hardwares to earn a living. They usually prefer payment in cash in order to avoid payment of any taxes. South Africa has been one of the continent's top destination for Chinese investment for years. China malls and other less formal business have mushroomed everywhere in the cities and even as far as remote villages. Some of these businesses also prefer payment by means of cash.

The Global Corruption Barometer Africa (2019) reveals that 64% of South Africans believe that corruption has increased in 2018 and 70% thinks that the government is not doing enough to tackle corruption. State capture has become the buzzword in most citizens' lips. The perceived high levels of corruption is discouraging citizens to pay their taxes (New York Times, 2018).These and other factors serve as a fertile ground for SE activities.

The inability of the South African tax authority to meet its yearly tax revenue has further fuelled speculation that the formal economy might be losing out to the informal economy. Tremendous pressure has been mounting on the tax authority to quantify the size of the SE to enable targeted enforcement actions (Lol, 2019).

It is against this background that this study was initiated. This paper aims to contribute in understanding the development and size of the SE in South Africa for the period 2004 to 2018.The paper will only focus on the legal activities that would ordinarily contribute to the country's GDP. To our knowledge, this is one of the first comprehensive study to combine the Currency Demand Approach and the MIMIC model to estimate the size of the SE in South Africa.

The rest of this paper is organised as follows. Section 2 presents the literature review. Section 3 shows the theoretical models. Section 4 provides the model results and analysis. Section 5 shows the discussion. A conclusion is shown in section 6. Finally, appendices are provided in section 7.

Literature review

Many developing countries are struggling to measure the SE mainly because of the ambiguity in its definition and the fact that it is so closely intertwined with the formal economy. SE is sometimes referred to as the underground economy, illicit economy, hidden economy, grey economy, black economy, unrecorded economy, cash economy and informal economy. It may refer to either illegal activities or legal activities, which were not subjected to taxes or the required licenses (Hall, 2019).

Medina & Schneider (2019) defines the shadow or informal economy as all economic activities hidden from the official authorities for monetary, regulatory and institutional reasons. Monetary reasons could be avoiding paying taxes and all social security contributions, regulatory reasons could be the regulatory framework burden or government bureaucracy and institutional reasons include the weak rule of law, corruption law or the quality of political institutions.

SE activities can be either legal or illegal. Sharapenko (2009) refers to a definition proposed by Popov (1999) which defines the SE as the aggregate of illegal economic activities that feed felonies of different degrees. The author concentrates on the illegal activities of the economy, which would not necessarily be subjected to taxes and are therefore not the focus of this research paper.

There are various methods used to measure the SE but can generally be divided into two categories namely: direct and indirect approaches.

Direct approaches

These microeconomic approaches rely on surveys and tax auditing. The main advantage of surveys is the wealth of information that can be obtained on the structure of the SE. However, surveys are dependent on the honesty of the respondents and their willingness to disclose any illicit activities. The results from surveys are sensitive to the way the questionnaires were formulated which also affects the comparability of the results across countries. Tax compliance data might be biased as the selection of taxpayers is not random but based on the likelihood of tax fraud and the estimates will only include the portion of SE discovered by the authorities and not all hidden activities (Medina & Schneider 2018; Schneider & Buehn, 2016).

Indirect approaches

These are macroeconomic approaches that use various economic and other indicators that contain information about the development of the SE over time (Schneider & Buehn, 2016; Schneider & Enste 2000; Medina & Schneider 2018). The six main indirect approaches are:

- The discrepancy between national expenditure and income statistics

In national accounting, the income measure of Gross National Product (GNP) should equal the expenditure measure of GNP. The discrepancy between the expenditure measure and the income measure can be used as an indicator of the extent of the SE.

- The discrepancy between official and actual labour

A decrease in the labour force of the formal economy can indicate increased activity in the SE. However, these estimates are perceived as weak indicators of the size and development of the SE as individuals can simultaneously participate in the shadow and formal economies (Schneider & Buehn, 2016).

- The transactions approach

This approach is based on the assumption that there is a constant relation over time between the volume of transactions and official GNP. The main disadvantage of this method is that precise figures of the volume of transactions is not easily available especially for cash transactions. Furthermore, an assumption is made that the gap between the volume of transactions and GNP is due to SE which might not necessarily be the case (Schneider & Buehn, 2016).

- The physical input method (electricity consumption)

This method involves two approaches namely: The Kaufmann – Kaliberda (1996) Method and the Lackó method. In the Kaufmann - Kaliberda method, electric power consumption is used as an indicator of the overall economic activity of a country. Lackó (1999, 2000a, b) assumes that a certain part of the SE is associated with the household consumption (HHC) of electricity.

- The Currency Demand Approach

Originally formulated by Cagan (1958), this approach assumes that SE activities are conducted using cash. An increase in the size of the SE will therefore increase the demand for currency (Schneider & Buehn, 2016). Although widely used, this approach has the following disadvantages:

➢ This approach may underestimate the size of the SE as not all transactions in the SE are conducted in cash.

➢ The absence of reliable data such as tax morality is a challenge.

- The MIMIC Approach

The MIMIC model is a special type of structural equation modelling (SEM) based on the statistical theory of unobserved variables (Hassan & Schneider, 2016). This model is confirmatory as it confirms the influence of a set of exogenous causal variables on the latent variable (SE), and the effect of the SE on macroeconomic indicator variables (Farzanegan, 2009).The MIMIC model has the following advantages:

- Considers multiple indicator and causal variables at the same time.
- Flexible - varies causal and indicator variables depending on the particular features of the SE activity.
- Uses maximum likelihood (ML) estimation procedures, which are well known and are generally optimal if the sample size is large enough.
- Does not need any restrictive assumptions to operate.
- Can be applied to other informal economic activities not only the SE activities.

The main disadvantages of this model is in its confirmatory nature i.e. it confirms a given model and does not find a suitable model. The benchmarking procedure requires experimentation, and a comparison of the calibrated values in a wide academic debate. No consensus exists on the most reliable benchmarking procedure.

The two used theoretical models

MIMIC model

The multivariate indicators multivariate causes (MIMIC) model refers to the type of models that involve a set of indicators and a set of causals variables. This type of regression involves multiple equations and can also include some unknown variable(s) to be solved or estimated from the observed variables provided there is a theoretical relationship between the variable(s). Thus, one needs to consider a theoretical relationship or a hypothetical relationship between the unobserved, causals and the indicators to be included in the model

The MIMIC model with unobserved (latent) variables are special type of models based on the covariance among variances to estimate the latent variable. Hence this models are sensitive to the data skewness and outliers (Gana & Broc, 2019). The transformation of data to normality becomes crucial in order to obtain reliable model results. The theoretical hypothesis concerning the variables included and the direction of the relationship should be the foundation as several models could best fit the latent variable hence the relationship is spurious.

Nevertheless, the aim of the MIMIC model with latent variable is to obtain a model whose covariance matrix approaches or mimic the observed sample covariance matrix (Hassan & Schneider, 2016). The model is divided into two parts, which are the Measurement and the Structural equation model. The measurement part of the model includes a set of indicators and the structural equation consists of causal variables.

The mathematical representation of the MIMIC model with latent variables is shown in equation 1 and 2.

$$Y_i = \lambda_i \eta + \varepsilon_i, \ i = 1, \dots, n \tag{1}$$

Equation 1 above is the measurement model where:
Y_i represents a vector of indicators,
λ_i represents the regression coefficients,
ε_i represents a vector of white noise errors, and
η represents the latent variable

$$\eta_t = \alpha_1 X_{1t} + \alpha_2 X_{2t} + \cdots + \alpha_p X_{pt} + \varepsilon_t \tag{2}$$

Equation 2 above is the structural equation model (SEM) where:
$X_1, X_2, \dots, X_p$ represents exogenous causal repressors,
$\alpha_1, \alpha_2, \dots, \alpha_p$ represents the model coefficients,
η_t represents the unobserved or latent variable, and
ε_t represents the model error term

From equation 1 and 2, the general structure of the MIMIC model can be represented by Figure 1 below;

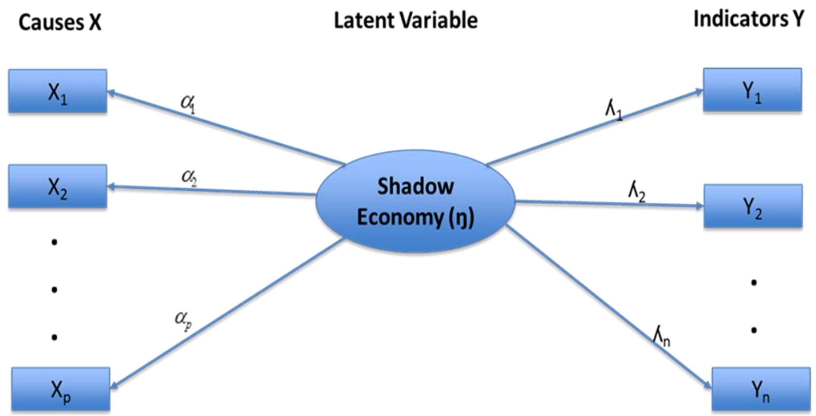


Figure 1. *General structure of a MIMIC model*

However, the MIMIC model only generates the fitted indices and requires prior estimation of the size of the SE to be available. Thus, to obtain the series of estimates for the latent variable a benchmark procedure shown in equation 3 is used.

$$\hat{\eta}_t = \frac{\tilde{\eta}_t}{\eta_{base\_year}} \eta * base\_year \qquad (3)$$

where:

η_{base_year} represents the value of the MIMIC index in thebase year,

$\eta * base\_year$ represents prior estimation of the size of the shadow economy in South Africa in the base year

$\tilde{\eta}_t$ represents the value of the MIMIC index at time t,

$\hat{\eta}_t$ represents the SE at time t

The causal variables considered in the case of South Africa are discussed in the following section.

Causal variables

a. Tax burden

This is the most important and widely used variable affecting the size of the shadow economy. A considerable amount of studies confirms a highly significant positive effect of tax burden on the shadow economy (Amoh & Adafula, 2019; Ariyo & Bekoe, 2012; Klaric, 2010).

Taxes increase the production costs of goods and services, which translates into a higher selling price in the formal market. As a way of increasing one's wealth, individuals might be tempted to evade tax. Therefore it is reasonable to assume that the greater the tax burden, the greater the willingness to evade it and underground and informal production is more likely to occur.

Hypothesis: The higher the tax burden, the larger the size of the shadow economy, ceteris paribus.

b. Business regulations

A highly regulated economy may reduce choices available to individuals and might lead them into the informal economy. Regulations such as barriers to entry and certain policies can drive businesses to consider trading in the informal economy (McMillan, 2006). In the South African context, most regulations such as the Black Economic Empowerment (BEE) were introduced to redress the imbalance of the past brought about by the apartheid government. According to Frontier Economics (2012), regulations introduced to address equality and social cohesion are most likely to have a negative impact on the formal economy. Empirical studies such as Schneider (2005), Enste (2005) and Schneider & Hametner (2007) suggest that increased regulation leads to a growing SE.

The South African economy is somewhat oligopolistic in that there are only a few players in different economic sectors because of the high level of regulation in some sectors. For example, the South African banking sector is mainly dominated by five or so commercial banks while, for instance, the Kenyan banking industry comprises of about 43 commercial banks. Currently, Kenya has one of the fastest growing economy in Africa as a result. Regulation is one of the factors that determines the ease with which businesses operates.

Hypothesis: The higher the regulations in an economy, the higher the SE activities, ceteris paribus.

c. Unemployment

Unemployment has an ambiguous effect on SE. Schneider & Hametner (2007) and Dell'Anno *et al.,* (2007) established that unemployment can influence individuals to operate in the SE to find jobs. If individuals cannot find work in the formal economy, they will look for it in the informal one. In such cases, SE can offer them relatively higher income as no taxes are paid.

On the other hand, Hassan & Schneider (2016) showed that in the Egyptian economy unemployment does not affect the development of the SE over time as the availability of jobs in both informal and formal economy is limited due to the continuous contraction of the overall economy.

In the case of South Africa, the persistent rise in unemployment can directly contribute to the increase in SE as people who get unemployed or laid-off from the formal economy seek alternative means of survival in the SE.

Hypothesis: The higher the unemployment, the larger the size of the shadow economy, ceteris paribus.

d. Self-Employment

The rate of self-employment as a percentage of labour force in the formal economy is regarded as one of the factors influencing the shadow economy (Hassan & Schneider, 2016). A rise in self-employment increases the potential number of opportunities to conceal income from the authorities (Dell'Anno *et al.,* 2007). Currently, over 10% of South Africa's workforce is self-employed. Due to the difficulties faced in the South African job market, another dominant cause of the rise in self-employment is the lack of finding jobs. Other reasons include unhappiness at traditional jobs, desire for greater flexibility, choice of own workspace or constant conflict with managers or colleagues. Over the last few years, there has been a significant mind-set shift and with it has emerged a workforce, which values flexibility over stability. It has led to an increased entrepreneurial activity in the South Africa (Koekemoer, 2018).

Hypothesis: The higher the self-employment rate, the larger the size of the shadow economy, ceteris paribus.

e. Household debt

If individuals become indebted, they are more likely going to avoid paying taxes as tax is not amongst the priority items on which household income would be spent. South Africa has a higher rate of debt to disposable income ratio, this will most likely tempt heavily indebted households to look for other sources of income to supplement the main income, and this additional income will often not be declared.

Hypothesis: The higher the household debt, the increase in the SE activities, ceteris paribus.

f. Government employment

The expected sign for this indicator is ambiguous. Some authors find a negative relation arguing that in some sectors the presence of the state could disincentive people to incorporate in the SE. In South Africa, the government wage bill is considered very high and the current government is considering laying off some of the aging and unproductive workforce. Retrenchments and early retirement packages will in most likelihood result in laid off workers engaging in SE activities.

Hypothesis: The lower the government sector, the larger the SE activities.

However, other papers find a positive relation arguing that a rise in the size of the public sector gives relevant incentive to enter in the informal sector. Dell'Anno (2007) states that most researchers support a decreasing role of the public sector in the economy. An increased public sector means that government officials have more power over decisions and will result in more corruption. Schneider & Enste (2002) agrees by stating that bribery and dishonesty of civil servants is another determinant of the SE.

Hypothesis: The larger the government sector, the larger the SE activities, ceteris paribus.

g. Size of mining sector

The mining sector plays a significant role in the South African economy. According to the UNCTAD report (2016), South African miners of silver, platinum group metals, gold and iron ore had systematically and fraudulently indulged in mis-invoicing in order to evade taxes and other legal obligations.

The emergence and growth of illicit mining activities in South Africa contributes to the growth in the SE as most if not all the output is sold in the black market as the miners and people they supply are most likely not licensed to trade in the commodities extracted.

Hypothesis: The lower the formal mining sector activities, the higher the SE activities, ceteris paribus.

Indicator variables

a. GDP

Existing literature indicates that there is an ambiguous relationship between formal economy and the shadow economy (Hassan & Schneider, 2016). An increase in the size of the SE leads to a decrease in the official economy because productive resources and factors are absorbed by the SE creating a depressing effect on the growth of the official economy. The lower the GDP, the most likely it is that the people will look for opportunities in the SE (Buehn & Farzanegan, 2013; Schneider & Enste, 2013; Dell'Anno *et al.,* 2007).

Hypothesis: The larger the size of the SE, the lower the GDP, ceteris paribus.

Other authors such as Schneider *et al.,* (2003) find a positive relationship between formal and informal economy. The SE might allow poor people to find ways to produce and sell cheap products as a way of generating income. The increased demand in the informal economy spills over into the formal economy.

Hypothesis: The larger the size of the SE, the larger the GDP, ceteris paribus.

Schneider (2005) argues that the relationship is negative for developing countries and positive for the developed and transition countries.

b. Labour force participation rate

Labour force participation rate has an ambiguous effect on the SE. On the one hand, SE absorbs resources from the formal economy as human capital shifts to the SE. Therefore, there is a negative relationship between the labour force and the SE.

Hypothesis: The larger the size of the SE, the lower the labour force participation rate.

On the other hand, Dell'Anno (2007) found a positive significant relationship between the SE and labour force participation in Portugal. Registered labour force might conduct informal activities during holidays, after working hours or on weekends.

Hypothesis: The larger the size of the SE, the larger the labour force participation rate, ceteris paribus.

c. Currency in circulation outside the banks

The shadow or hidden transactions are mostly conducted in cash rather than with credit/debit cards, cheques or bank transactions in order to avoid detection by authorities. An increase in the size of the SE will therefore increase the demand for currency (Schneider & Buehn, 2016).

In South Africa, there has been an influx of foreigners who set up their businesses and prefer payment in cash. Some of traders in the growing number of China malls also prefer payment in cash. Therefore one can expect an increase in the shadow economy.

Hypothesis: The larger the size of the SE, the larger the currency in circulation, ceteris paribus.

Currency demand approach

A currency demand function can be written as:

$$C_0 = A(1+\theta)^{\alpha} Y_0^{\beta} \exp(-\gamma i) \tag{4}$$

Where C_0 stands forobserved cash and θ represents the incentive variable that motivates individuals to make hidden transactions. This is a key variable in the CDA and can be approximated by the tax burden or the intensity of government regulation. Y_0 is the official real GDP and $i$denotesthe interest rate or inflation rate representing the opportunity cost of holding cash. A, α, β, γ represents positive parameters (Cagan, 1958).

Data on the following variables was collected for possible inclusion in the CDA model: currency in circulation, nominal GDP per capita, tax burden, deposit interest rate, unemployment, self-employment and government employment per labour force (representing a regulatory indicator). Unemployment had very high correlation with GDP and government employment (approximately 90%), hence it was excluded from the model and deemed to be explained by the two variables. Government employment and self-employment were highly correlated (greater than 80%).

In order to capture the long-run relationships of the explanatory variables on currency demand, the following model was constructed:

$$C_t = \beta_0 + \beta_1 Y_t + \beta_2 TAX_t + \beta_3 REG_t + \beta_4 SELF_t + \beta_5 R_t + \varepsilon_t \tag{5}$$

with $\beta_1 > 0$, $\beta_2 > 0$, $\beta_3 > 0$,$\beta_4 > 0$and $\beta_5 < 0$

where C_t represents the natural logarithm of currency in circulation normalised by GDP

Y_t represents the natural logarithm of nominal GDP per capita

TAX_t represents the natural logarithm of total of tax revenues normalised by nominal GDP

REG_t approximated by public employment in relation to total labour force

$SELF_t$ represents the natural logarithm of the self-employment per capita.
R_t represents the natural logarithm of the deposit interest rate
ε_t represents the error term

$\hat{C}$, which is the amount of currency demand in both the formal and shadow economies, can be estimatedfrom equation (5). Setting the incentive variable (θ) to the minimum and leaving all the other variables unchanged, yields $\tilde{C}$. The difference between $\hat{C}$ and $\tilde{C}$ is the extra currency in the economy, referred to as EC. This is the illegal money used in the SE to conduct transactions. Assuming equal income velocity of currency (v) for both the shadow and the formal economy, the size of the SE is estimated by multiplying EC by the income velocity of currency gives the estimate of the SE v i.e.

$$Y_{informal} = EC * V \tag{6}$$

However, equal income velocity of currency only holds if β_1= 1. If β_1≠1, a correction method needs to be applied to the results to obtain accurate estimates of the SE. The following proposed method by Ahumada *et al.*, (2007) was applied:

$$\frac{Y_{informal}}{Y_{formal}} = \left[\frac{C_{informal}}{C_{formal}}\right]^{\frac{1}{\beta}} = \left[\frac{\hat{Y}_{informal}}{\hat{Y}_{formal}}\right]^{\frac{1}{\beta}} \tag{7}$$

where$Y$ is GDP ,$C$is currency and $\beta$is the income elasticity.

Econometric/empirical results and analysis

This section discusses the econometric/empirical results from both the CDA and MIMIC model. The main sources of data for the models were Statistics South Africa (STATSSA) and South African Reserve Bank (SARB). Quarterly data series from the period 2000 to 2019 was used for the analysis to derive the annual shadow economy estimates.

The analysis of the results includes the best-fit models, evaluation of the results or model diagnostic and the model estimates for the period of interest.

CDA model

Several variables such as unemployment rate, government employment, self-employment, HHC, household debt (HHD) and inflation rate were considered for inclusion in the model. However due to multi collinearity and non-stationarity of the variables, only tax burden, self-employment, government employment, deposit interest rate and nominal GDP were included in the model. The variables were tested for the presence of unit root using the Augmented Dicky-Fuller (ADF) test. Based on the results of the unit root test, the time series were non-stationary at level but after taking the first differences, the time series became stationary. Since the variables are all integrated of the same order I(1), Johansen cointegration test was used to test for cointegration. For this test, the optimal lag length was determined using a VAR model. The optimal lag length is 4 according to Hannan-Quinn (HQ) information criterion. Using a lag length of 4, the Johansen cointegrating equation test indicated a rank of 3 for both the trace statistic and the max-eigen value test at 5% critical value. It can then be concluded that at least3 cointegrating relationships exists between the variables in the long run.

The Vector Error Correction Model (VECM) can now be used as the stationarity and the cointegration requirements have been satisfied.

Fitted CDA model and model evaluation

Table 1 below shows the model results. All the variables are significant at 5% level. As expected, the VECM results from Table 2 above shows positive coefficient for tax burden, regulator indicator (government employment), self-employment. Contrary to expectation, a positive coefficientis observed for deposit interest rate. A negative coefficient is observed for GDP.

Table 1. *The results of the CDA model from 2001 to 2018*

Variables	Statistics
C	1.00
	-0.937
Y	(0.437)
	[2.14]
	0.190
TAX	(0.082)
	[2.32]
	0.659
REG	(0.323)
	[2.04]
	0.092
R	(0.044)
	[2.08]
	0.339
SELF	(0.148)
	[2.29]
Constant	-0.005
	38.858
Autocorrelation LM test	p-value 0.342
Jarque-Bera (Normality test)	1.329
	p-value 0.515

Notes: All variables are in natural logarithms. Standard errors are in parentheses () and T-statistics in []. **Source:** Authors computation

There is no serial correlation of residuals as p-value of the LM test is greater than 0.05. The Jarque-Bera test indicates that the residuals are normally distributed.

Table 2 below shows the results for the cointegrating equations. The third error correction term indicates long-term causality between the variables.

Table 2. *Cointegrating equations*

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lncur_cgdp						
_ce1						
L1.	-.0176491	.2432886	-0.07	0.942	-.494486	.4591878
_ce2						
L1.	.1782368	.0549109	3.25	0.001	.0706134	.2858602
_ce3						
L1.	-.6609272	.2297285	-2.88	0.004	-1.111187	-.2106676

Source: Authors computation

CDA shadow economy estimates

Based on the results above, the estimates of the size of the SE are shown by Figure 2 below.

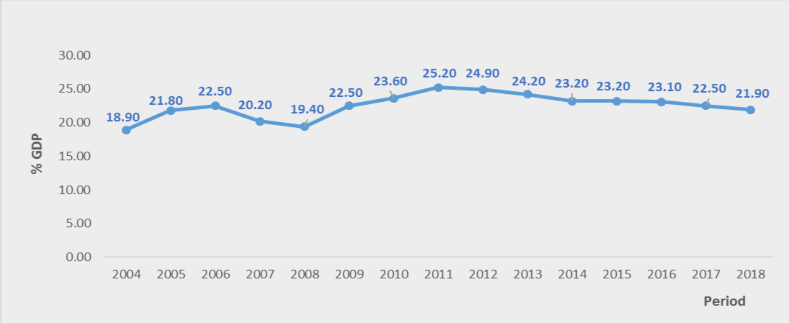


Figure 2. *Size and development of the South African SE as % of GDP using CDA*
Source: Authors computation

The CDA model estimates the SE to be 22.47% on average for the period 2004 to 2018, with the minimum value of 18.90% in 2004 and the maximum value of 25.20% in 2011. The estimates have been marginally decreasing from 2012 and the figures are stable around 22%.

MIMIC model

The three indicators considered to explain the shadow economy activities were nominal GDP, labour force participation rate (LFR) and currency in circulation (CURRENCY). Five causal variables were found to be significant in explaining the SE activities namely; tax burden (TAXB), household income (HHI), HHD & Unemployment (UNEMP) interaction, HHC and the sector mining GDP. These were all expressed as a percentage of total GDP at current prices. The variables used in the MIMIC model were transformed to be normally distributed and stationary for better model fitting.

The initial data set included other causal variables such as Consumer price index (CPI), social benefits, total government subsidies, government employment, finance GDP, agriculture GDP and interest rate. However, at 5% level of significance, the model considered those variables insignificant in explaining the SE activities.

Fitted MIMIC Model

Table 3 below shows the accepted MIMIC model with three indicators namely, nominal GDP, Currency and LFR and five causal variables namely, TAXB, HHI, HHD,UNEMP, HHC and the sector mining GDP, all expressed as a percentage of nominal GDP.

The indicators GDP, Currency and LFR from the measurement model are highly significant i.e. less than 1% level of significance. Both Currency and LFR have positive coefficients, indicating a direct relationship with the SE. However, GDP shows an opposite relationship with the SE.

The structural equation model, which links the causal variables to the SE, indicates that TAXB, HHI, HHC and the interaction of Unemployment & HHD (UNEMP*HHD) are positively related to the SE activities, implying that an increase in any of those causal variables will results in an increase in the SE activities.

The mining sector was highly significant in explaining some movements in the SE activities. When the mining sector GDP decreases, the SE activities increases (an indirect relationship). This shows the uneven share of resources from mining sector and the informal sector in South Africa.

Table 3. *MIMIC model results*

Measurement Model				
	Estimate	Std.Err	z-value	P(>|z|)
n =~				
LFr	0.201	0.060	3.316	0.001
C_CGDP	0.489	0.075	6.556	0.000
CGDP	-0.062	0.010	-6.357	0.000
Structural Equation Model				
	Estimate	Std.Err	z-value	P(>|z|)
n ~				
TAXB	0.405	0.123	3.297	0.001
HHI_CGDP	0.160	0.079	2.029	0.042
HHD*UNEMP	0.034	0.010	3.564	0.000
HHC_CGDP	0.333	0.083	4.022	0.000
MINGDP_CGDP	-0.916	0.287	-3.195	0.001
Statistical Test				
Root Mean Square Error of Approximation (RMSEA)				0.044
Standardized Root Mean Square Residual (SRMR)				0.022
Comparative Fit Index (CFI)				0.995
Tucker-Lewis Index (TLI)				0.986

Notes: n: Latent variable / Shadow economy. LFR: Labour force participation rate. CURRENCY: Currency in circulation per current GDP. CGDP: Nominal gross domestic product. MINGDP: Mining GDP. TAXB: Tax per GDP (Tax burden). UNEMP: Unemployment per labour force. Household Income (HHI), Household debt (HHD) and Household consumption (HHC) are as % of GDP
Source: Authors computation

MIMIC model evaluation

Several statistical tests exist for selecting the best fit model(s). The following statistics were used: Root Mean Squared Error of Approximation (RMSEA), Standardized Root Mean Square Residual (SRMR), Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) statistics to select the best fitting MIMIC model as presented in table 4.3.

The value of the RMSEA in Table 4.3 is 0.044 with a p-value of 0.449 ($p > 0.05$) signifying that the model of choice has a closer fit. The SRMR of 0.022 was observed, this statistic works similar to RMSEA but on the standardized data. CFI computed by the model was 0.995 greater than the acceptable value of 0.9. Furthermore, the TLI of 0.986, which is greater than the acceptable value of 0.9, was observed from the model fitted. The TLI statistic is more restrictive than the CFI. Based on the fitted MIMIC model, the SE estimates where derived as a percentage of nominal GDP and are presented in the next section.

MIMIC shadow economy estimates

The MIMIC model depends on some pre-determined SE estimate for the base year from another model. The base year of 2010 was chosen to align with the base year of the observed causal variables from STATSSA. This paper uses the predetermined own computation estimate of 23.6% for the base year from the CDA in section 4.1 above. The South African SE estimates are shown in Figure 3 below.

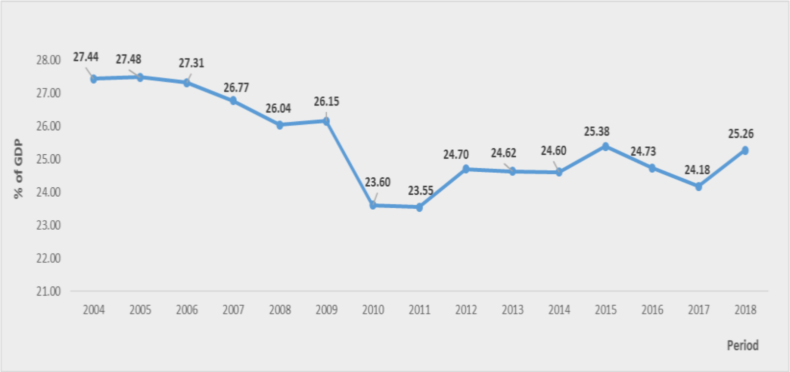


Figure 3. *The size of the SE in RSA as % of GDP – MIMIC Model*
Source: Authors computation

Using the 2010 base estimate of 23.6% from CDA model, the MIMIC model estimates the South African SE to be 25.45% on average for the period 2004 to 2018, with the minimum value of 23.55% in 2011 and maximum value of 27.48% in 2005. A gradual overall decreasing trend in SE is observed from the fitted MIMIC model.

Discussion

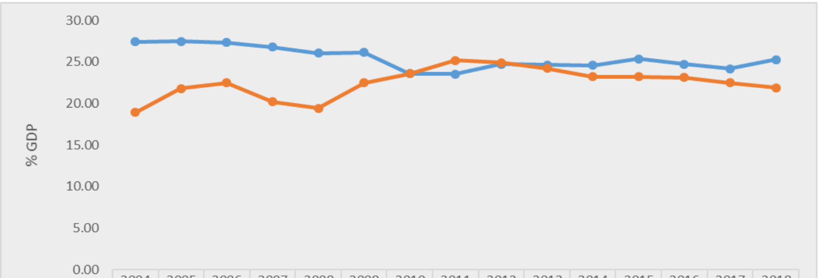
This chapter uses the scientific "indirect" methods, which are CDA and the MIMIC model to estimate the size of the SE in South Africa. The two models estimate the SE using economic indicators at macro-level and are viewed to be superior when compared to direct methods such as surveys and tax auditing (Giles & Tedds, 2002; Hassan & Schneider, 2016).

The sample data from 2000Q01 to 2019Q03 was initially used for fitting the two models. However, due to lack of complete data in other variables and the non-normal nature of some variables (even after transformation), the estimates were only generated from 2004 to 2018.

The MIMIC model was evaluated using the commonly used statistics, Root Mean Squared Error and the Comparative Fit Index CFI (with the benchmark value of 0.9). The value of the RMSEA was 0.044 significant at 5% level of significance. The CFI computed by the model was 0.995, greater than the acceptable value of 0.9. Based on the fitted MIMIC model, the SE estimates where derived as a percentage of nominal GDP.

Similarly, the CDA model residuals were evaluated to check for autocorrelation and normality. The probability values indicates the absence of autocorrelation and normal distribution of the residuals at 5% level of significance.

Figure 4 below compares the size of SE estimated from MIMIC and CDA.



	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
MIMIC	27.44	27.48	27.31	26.77	26.04	26.15	23.60	23.55	24.70	24.62	24.60	25.38	24.73	24.18	25.26
CDA	18.9	21.8	22.5	20.2	19.4	22.5	23.6	25.2	24.9	24.2	23.2	23.2	23.1	22.5	21.9

Figure 4. *MIMIC vs. CDA estimates comparisons*
Source: Authors computation

The average estimated size of SE from the CDA and MIMIC model for the period 2004 to 2018 are 22.47% and 25.45% respectively. This is a difference of 2.98% between the two models, thus the models discrepancies are minimal on average. The estimated range was 23.55% to 27.48% for MIMIC and for the CDA estimates were between 18.90% and 25.2%. Therefore, the overall estimates for the CDA models were a bit lower than those from the MIMIC model.

Conclusion

The CDA and the MIMIC models were derived and evaluated for better model fitting to estimate the South African shadow economy. According to the CDA, on average the SE accounts for 22.47% of the formal economy and according to the MIMIC model, the SE accounts for 25.45% on average. The discrepancy between the MIMIC and CDA model was around 2.98% on average for the period 2004 to 2018. Overall, both the models show a slight decreasing trend for the period.

As can be observed from Table 4 below, all the hypotheses were confirmed by both the CDA and the MIMIC model with the exception of the deposit interest rate. In South Africa's case, CDA model suggests that individuals will transact in cash despite the increase in deposit interest rate. Therefore the increase in deposit interest rate does not serve as a motivation to stop engaging in the SE activities.

Regulation could result in either a positive or a negative relationship with shadow economy. In our case, the model suggests that the growth in the government sector will result in more activities in the shadow economy due to government employees being susceptible to bribery and corruption. GDP could also have a positive or negative relationship with the shadow economy. The model results confirms Schneider (2005)'s assertion that the relationship is negative for developing countries. Similar results were obtained for mining sector GDP. The relationship between unemployment and shadow economy was insignificant. The relationship became positive and significant, only when unemployment interact with HHD.

Table 4. *Empirical confirmation of the hypotheses*

Variables (Hypothesized sign)	Method	Result
1. Total tax burden (+)	CDA MIMIC	Both Confirmed
2. GDP (-)	CDA MIMIC	Both Confirmed
3. Self-Employment (+)	CDA	Confirmed
4. Regulation (+)	CDA	Confirmed
5. Mining sector GDP (-)	MIMIC	Confirmed
6. Labour force participation rate (+)	MIMIC	Confirmed
7. Currency (+)	MIMIC	Confirmed
8. Household debt (+)	MIMIC	Confirmed
9. Unemployment (+)	MIMIC	Confirmed

The results from this study are just the first step of understanding the overall SE activities and could be used by the government authorities of South Africa for decision making on a high level. However, there is a need for further analysis to be done to explore the SE activity distribution between different economic sectors in order to influence future enforcement plans and undertakings by government authorities; resulting in an easier way to identify, locate and monitor unrecorded businesses and also maximise revenue collections and minimise non-compliance for different sectors.

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6 A neural network-based approach for the study of the decision-making process within a company

Mouna **Bekri** [a] [†]
Ahmed **Hachicha** [b]

Introduction

In fact, reasoning and learning are two main aspects of human cognition. The former is the process of using previously acquired knowledge to solve the encountered problems. Moreover, this process can be simulated using heuristic research (Deuris, 2018). Learning, which is considered as a knowledge acquisition process, can be simulated using artificial neural networks (Rasheed *et al.*, 2017). In order to imitate human cognition, some machines are used for the imitation of reasoning while others are for the imitation of learning ability. Although reasoning can be imitated by symbolic reasoning techniques, learning ability

[a†] LED, Faculty of Economics and Management of Sfax, 4 Airport Road, 3018 Sfax, Tunisia.
☎. 0021698994448 ✉. bekrimouna0@gmail.com
[b] University of Sfax, LED, Faculty of Economics and Management of Sfax, 4 Airport Road, 3018 Sfax, Tunisia.
☎. 0021655110522 ✉. Hachicha.Ahmed@fsegs.rnu.tn

can be imitated by machine learning techniques. In reality, the integration of symbolic reasoning and machine learning in an effective way has remained difficult until today (Garcez *et al.,* 2015). However, several research studies have been carried out to treat symbolic reasoning using formal methods to model reliable reasoning processes (Chang & Lee, 1973). Similarly, several other studies have been carried out to treat machine learning using deep data-based architectures (Lecun, *et al.,* 2015; Mohamed *et al.,* 2012; Sun *et al.,* 2015). These two processes are independent but the links between them are very weak. Therefore, it is difficult for a machine to imitate both symbolic reasoning and learning skills. For this reason, artificial neural networks (ANN) have been seen as a solution to this and therefore, have invaded all areas of research. In fact, they are mathematical models that are inspired by the structure and functional aspect of the biological neural system. Moreover, their integration affects our daily life (transport, natural language processing, facial recognition, etc.) using data (Vlahogianni *et al.,* 2015; Chen *et al.,* 2016). Their versatile architectures make them more suitable for handling large volumes of unstructured data (Maren *et al.,* 2014).

Litrature review

Artificial neural networks are inspired by the structure and functional aspect of the biological nervous system. A first wave of interest in neural networks (also called connectionist models or parallel distributed processing) appeared after the introduction of neurons by McCulloch & Pitts (1943). The first neural networks were designed by Rosenblatt in 1958. They are linear and monolayers inspired by the visual system. Their learning is supervised and the input data is continuous, which is referred to by the perceptron algorithm which can compute a large number of Boolean functions but not all of them. In fact, in 1963, R.W.

Hamming used binary input data and supervised learning. Then, a network known as the Hamming network appeared. Around 1982, Kohonen inspired the mammalian perceptron nervous system to operate the Kohonen network and look for the neuron model closest to reality. He modeled the law of lateral interaction where the nearest neurons positively and negatively interact with the furthest one. On the contrary, the Hopfield network considers that neurons have two states, either -1 and 1 or 0 and 1. Its learning law follows the rule of Hebb (1949) who considered that the synapse activity (connection between neurons) is improved once the neurons are activated simultaneously. In 1988, a supervised network of multilayer perceptron was created. This network contains several intermediate layers which are the hidden layers. Each neuron is linked to all the neurons of the previous and next layer. It follows a gradient back propagation algorithm, which is a gen of ANN structured into groups of neurons interconnected by means of so-called connection channels (or synapse) (Bishop, 1995) where each connection is associated with a weight. These neurons are organized in three classes of layers; input, hidden and output. The input layer neurons receive input data where each neuron receives a set of inputs which correspond to the outputs of the neurons of the previous layer and outputs a weighted sum of its inputs to the neurons of the next layer to which it is connected. Then, the weighted connections enable the model to know the relationships between variables. For the hidden and output layer neurons, an activation function is applied to these input values (Han *et al.,* 2011). The commonly used activation functions are the sigmoid, hyperbolic tangent, Gaussian and threshold functions. The output layer returns result after compilation of the data entered by the first layer realization of the Widrow-Hoff rule.

On the other hand, a single feedback neural network is made up of an input layer, a hidden layer and an output layer while more complex deep neural networks are made up of more than one hidden layer each of which uses the output of the previous layer as input (Pal & Mitra, 1992). Although the layers can only process simple data, the following ones can recognize more complex data by combining the results of the previous treatments, which implies that these networks are the most efficient.

In general, the most important characteristic of RNA is their learning skills. In fact, networks are understood by following a learning algorithm that can be either supervised or unsupervised. The former consists in providing the desired results to the network so that it adjusts its connection weights to obtain the results closest to the desired results while the latter consists in providing only the input data but not any information on the output results.

Although the ANNs come from the neurons and computer fields, today they extend to other research disciplines (Maren *et al.,* 2014). This rapid expansion is explained by what is called "Big Data". The combination of large amounts of unstructured data, on the one hand, and the versatile architecture of ANNs, on the other hand, which led to many revolutionary results in a variety of disciplines, such as facial and voice recognition, genetic detection autism and natural language processing…

The use of neural networks in business, finance or management has been examined by several authors from different perspectives. For instance, Wong *et al.,* (1997) focused in their studies of RNA during the period 1988 and 1995 on the commercial field. In fact, they grouped the articles of this period into 12 categories according to their field of application and their means of development ... A year later, Wong & Selvi (1998) concentrated their studies on the application of ANN in the financial field during the period from 1990 to 1996. They found that most of the articles that dealt with NASA forecast bankruptcy and poor performance. In the same period, the work of Vellido *et al.*, (1999) related to the application of NAS to management, marketing or decision-making and financial use, such as bond ratings, derivatives, stock markets and macroeconomic forecasting. On the other hand, Forgeron & Gupta (2000) presented interesting developments in the use of artificial intelligence for operational research problems. They highlighted the different types of ANN models that are applicable to solve business problems.

A great deal of research studies have been carried out in the past two decades. In fact, in recent decades the growth recognized in the ANN applications has contributed to a massive development and expansion of information technology, which led to better applicability of artificial intelligence methods in scientific studies. In addition, numerous software programs have been introduced enabling users with minimum skills and programming to design and test RNAs for specific problems. The researchers applied RNA to solve several problems. Then, using binary variables in auditing and accounting, Etheridge *et al.*, (2000) and Gaganis *et al.*, (2007), showed how various ANNs can reduce the costs of classification errors in the auditor's judgment on a client's financial viability. In general, the categorical learning network has been more successful in classifying bankrupt banks because incorrectly classifying a bankrupt bank as healthy could be much more costly than vice versa. The obtained results provided additional evidence to Lenard *et al.*, (1995) who argued that hidden patterns of financial data strongly affect decision-making in the auditing process. As for Chen *et al.*, (2011), they proposed an automatic detection system to analyze erroneous tax declarations in construction companies using several variations of neural networks. In 2012, Brown and Mues compared various approaches to credit rating to that of NAS. For their part, Blanco *et al.*, (2013) set up RNAs for microfinance credit while Leong (2015) proposed a Bayesian network model to solve the problems of implementing credit scoring in real time. Emotional RNA has also been suggested as an appropriate tool for credit analysis. Despite the successful requests, there are some issues when using neural networks in credit scoring, including pre-processing of input data or determining the ratio between learning and validation samples. On the other hand, Lee *et al.*, (2008) and Lee & Shih (2009) focused on the behavior of consumers seeking medical services, while Baesens *et al.*, (2004) identified the slope of clients' life cycles. They presented the Bayesian network as a probabilistic technique capable of capturing the high order relationships between sets of variables in a binary classification. In the area of financial analysis, Abdou *et al.*, (2012) explored the determinants of capital structure in the retail industry whereas Chiang *et al.*, (1996) analyzed the net asset value of a mutual fund then, Kryzanowski & Galler (1995) examined the financial statements of small businesses. As for Cao & Parry (2009), Etemadi *et al.*, (2015) and Zhang *et al.*, (2004), they concluded that neural networks can significantly improve the accuracy of earnings per share forecasts. Their results also indicated that the models composed only of lagged dependent variables had a lower explanatory power than the included models of fundamental accounting variables. Moreover, it should be noted that the financial sample size for analysis applications was generally smaller than that of other business disciplines.

In fact, each activity was affected by various decisions. Therefore, the fact of having a reliable decision becomes an essential issue for each company in a fluctuating environment. Compared to previous surveys on business ANNs, we noted a strong increase of the number of decision support applications. In one of the reviews, the ANNs have provided many advantages over traditional models, particularly in the case of complex and non-linear data. Then, in 1997, Li *et al.,* (1997) proposed an intelligent generator of future scenarios for the planning of future activities which overcame the limits of conventional methods in terms of learning capacity. Besides, Thieme *et al.,* (2000) successfully compared the ANNs to the ordinary least squares method and discriminant analysis in the development decision, while West *et al.,* (2005) focused on the applications of financial decisions. On the other hand, the ANNs in the decision support systems did not provide clarification on the impact of the inputs, as a result, they lost their generalization capacity. As for Davis *et al.,* (2001), Yu *et al.,* (2008) applied the NAS to predict the magnitude and direction of changes exchange and interest rates. Then, Hu & Tseng (2007), Chauhan, *et al.,* (2009) and Jeong, *et al.,* (2012) integrated the ANN and meta-heuristic techniques to achieve better performance in bankruptcy forecasting tasks. Some years before, Bloom (2005), Fish *et al.,* (1995), Cuadros & Domínguez (2014), Baesens (2004), Crone *et al.,* (2006), and Olson & Chae (2012), took a direct interest in marketing while Gómez-Pérez *et al.,* (2009) sought an optimal policy for campaign marketing. Moreover, Thomassey & Happiette (2007) designed an ANN, as an automated sales forecasting system based on data from a textile distributor. Before that, Alon *et al.,* (2001) Kuo & Xue (1998) and Kuo *et al.,* (2002) focused on the integration of conventional and fuzzy NAS to improve a solution to the problem of forecasting sales on promotion.

In fact, the increasing use of ANN techniques can be attributed to their flexibility and ability to significantly outperform other data mining methods (LeCun *et al.,* 2015). These techniques were used to solve real world problems in various research fields, such as image classification

(Krizhevsky *et al.,* 2012; Hu, *et al.,* 2018), voice recognition (Dahl, *et al.*, 2012) and bio-informatics (Lusci, *et al.,* 2013; Xu *et al.,* 2015). The use of the -NAS for demand forecasting is also on the rise, some studies have been published on research topics, such as transport systems (Ke *et al.,* 2017; Huang, *et al.,* 2014), hospital management (Jiang *et al.,* 2017) and the electrical charge (Qiu *et al.,* 2017).

Methodology

In the context of data processing, the ANN constitutes a method of complex system approximation. Their approximation capacities have proven their capacity to extract experimental data from efficient models without having to hypothesize about the general shape of these models (Bloch, 1999).

The most widely used ANN family is the multilayer perceptron (MLP), which mimics the functioning of the human brain at two points; knowledge is acquired through a learning process and the weights of connections between neurons are used to memorize knowledge. As already mentioned, this network is made up of three types of layers; the input, hidden and output layers.

Since there are theoretical rules that enable to determine the optimal architecture of a neural network, several authors, such as Wierenga & Kluytmans (1994), Venugopal & Baets (1994), proposed empirical rules which consist in realizing a number of tests by varying the number and size of the intermediate layers.

However, as with any neural application, a crucial point in the modeling phase remains the determination of the network structure. Indeed, even if the work of (Cybenko, 1989) showed that a single hidden layer using sigmoidal activation functions is sufficient to approximate any nonlinear function with the desired precision, nothing is said to a priori on the number of the used hidden neurons.

On the other hand, the decision-making process is a daily process taken by different actors (managers, executives, employees, workers, etc.) within a company. Each decision is made by taking into account several factors (characteristics of the organization, the used technology, market development, legal constraints, dynamics of social relations, the behavior, and the personality of the decision maker as well as his psychological profile, etc.). However, the decision maker tries to rationally evaluate all the alternatives before making his choice, which corresponds to a strict logic of profit maximization.

In fact, a careful examination of the data enables us to obtain indicators on the decision rules that can be used by managers within companies. In each task, the responders try to choose an optimal decision. The optimal decision differs from one to another. Some managers seek solutions to the encountered problems to meet their own needs and suit their personalities, their thoughts and their behavior. Others believe that an optimal solution is the one that brings the maximum profit, on the one hand, and the minimum risk, on the other hand. Some others choose a compromise decision and alternatives that guarantee their needs and ensure normal level of profit.

After this brief explanation, we could conclude that our model must respect four decision rules; profit maximization, risk minimization, which are suitable for the thinking of the decision maker, the most rational. However, the decision is influenced by several factors, such as the type, amount and characteristics of the information, thought, feeling and behavior of the decision maker, company's structure and the process of EKM.

Data

Our data were collected during the year 2019. The sample of our study is made up of 200 decision-makers, from different activity sectors of different ages, from different functions, and companies chosen at random. Table 1 shows the descriptive statistics of the responders. Table 2 shows descriptive business statistics.

Table 1. *Descriptive statistics of responders*

		Sex	Age	Education	Function	Experience
N	Valid	200	199	200	200	200
	Missing Mode	0	1	0	0	0
		1	3	4	1	4

Table 2. *Descriptive statistics of compagnies*

		Size	Legal status	Sector of activity	Company's structure	Zone
N	Valid	199	199	196	200	200
	Missing Mode	1	1	4	0	0
		2	1	7	1	2

Vaiables used to build the ANN

For the design of our artificial neural network, we choose as input neurons the responder status variables (age, gender, education, experience, function, rationality, behavior, thinking, etc.), company's structure (size, status, sector of activity, area...), information criteria (precision, cost, completeness, confidentiality, reliable, relevant, profitable and fast) and the IEKM process (data collection, information processing, knowledge creation and exploitation…).

Since the number of variables is quite large, we have restored a fairly large and difficult to interpret correlation matrix for this, we have reduced the number of variables to a limited number of factors. These help synthesize data from a cross between several variables. In order to simplify the data, the variables were treated according to dimensions which gather the maximum information offered by the initial variables. In addition, we processed each part of our data independently of the others, then we studied the relationships between the different components by regressing them through neural networks. In the end, we used the results of these regressions to build our final network in order to respond to our initial problem.

The independent variables are:

- Behavior of decision makers presented by the variables FAC1_1, FAC2_1, FAC3_1, FAC4_1, FAC5_1, FAC6_1, FAC7_1 and FAC8_1
- Company's structure presented by the variables FAC1_6 and FAC2_6.
- Characteristics of the information presented by the variable FAC1_2.
- Knowledge processing procedure presented by the variable FAC1_3
- Types of information presented by the variable FAC1_4
- Economic intelligence and knowledge management process presented by the variables FAC1_5, FAC2_5 and FAC3_5
- Decision characteristics presented by the variables FAC1_11, FAC2_11, FAC3_11, FAC4_11 and FAC5_11

Dependent variable is:

The output corresponds to choosing a decision from two supposed categories (optimal; the maximum profit, the minimum risk, suitable for the decision maker and the most rational or non-optimal).

ANN design and setup

The Multilayer Perceptron (MPL) module from IBM SPSS was used to build the neural network model and test its accuracy. The (MPL) neural networks are formed with a back-propagation learning algorithm that uses descent gradient to update the weights to minimize the error function.

The data were randomly distributed between the training (60%) tests (20%) and retention (20%) subsets. The training data set is used to find the weights and build the model. Test data is used to find errors and avoid overtraining during training mode. Resistance data is used to validate the model. The basic configuration of PMCs is summarized below:

*Multilayer Perceptron Network.

Optimal MLP decision (MLEVEL=N), with FAC1_1 FAC2_1 FAC3_1 FAC4_1 FAC5_1 FAC6_1 FAC7_1 FAC8_1 FAC1_2 FAC1_3 FAC1_4 FAC1_5 FAC2_5 FAC3_5 FAC1_11 FAC2_11 FAC3_11 FAC4_11 FAC5_11 FAC1_6 FAC2_6 v1 v2 v3 v4 v5

/RESCALE COVARIATE=STANDARDIZED

/PARTITION TRAINING=6 TESTING=2 HOLDOUT=2

/ARCHITECTURE AUTOMATIC=NO HIDDEN LAYERS=2 (NUMUNITS=AUTO) HIDDEN FUNCTION=TANH OUTPUT FUNCTION=SOFTMAX

/CRITERIA TRAINING=BATCH OPTIMIZATION=SCALED CONJUGATE, INITIAL LAMBDA =0.0000005, INITIAL SIGMA =0.00005 INTERVAL CENTER=0 INTERVAL OFFSET=0.5 MEMSIZE=1000

/PRINT CPS NETWORK INFO SUMMARY CLASSIFICATION IMPORTANCE

/PLOT NETWORK ROC GAIN LIFT PREDICTED

/SAVE PREDVAL

/STOPPING RULES ERROR STEPS= 10 (DATA=AUTO) TRAINING TIMER=ON (MAXTIME=15) MAX EPOCHS=AUTO ERROR CHANGE=1.0E-4 ERROR RATIO=0.0010

/MISSING USER MISSING=EXCLUDE.

For the hidden layer, hyperbolic tangent (or tanh) was used as an activation function: Oj=f(x)=$\frac{e^{X}-e^{-X}}{e^{X}+e^{-X}}$.

For the output layer, the softmax function was used as an activation function. The activation of the j[th] output neuron is Oj=f(x)= $\frac{e^{x}}{\sum_{i}^{m} e^{x}}$ where m is the number of output neurons. The softmax function takes real numbers as arguments and maps them into real values between 0 and 1, which have a sum equal to 1. Then, the layer using the softmax function can be considered as a probability distribution.

In fact, the gradient descent optimization algorithm can obtain the best solution with batch or online (or incremental) mode. Therefore, four parameters were used to determine how the scale-conjugate gradient algorithm constructed the model; initial lambda, initial sigma, interval center and interval offset. The lambda parameter controls whether the Hesse matrix is negatively defined. The parameter lambda controls if the Hessian matrix is negative definite. The parameter sigma controls the size of the weight change that affects the estimation of Hessian through the first order derivatives of error function. The range of center parameters forces the algorithm to generate random weights that are automatically updated to minimize the error function. Initial lambda was set to 0.0000005, initial sigma to 0.00005, then, the interval center was defined as 0 and the interval offset was set to ±0.5.

Stopping Rules:

- Maximum steps without decreasing the error: 10
- Maximum training time: 15 min
- Maximum training epochs: auto
- Minimum relative change in the training error: 1.0e-4
- Minimum relative change in the training error ratio: 1.0e-3

When the softmax activation function is applied to the output layer and the SPSS uses the cross-entropy error function instead of the squared error one that uses the other activation functions.

The cross entropy error function for one training example is given by the formula: $E= -\sum_{j}^{m} t_j \ln O_j$ where m is the number of output neurons, tj the output neuron value j and Oj the actual output value of the output neuron. Then, the back propagation algorithm in each iteration (or epoch) calculates the gradient of the training error as j $\frac{\partial E}{\partial Wij} = (O_j - t_j)X_h$ for the weights of neurons linking the hidden layer to those of the network output layer and the formula $\frac{\partial E}{\partial Wij} = (O_j - t_j)X_h W_{hj}(1-X_h) X_i$ for the weights of neurons binding the input layer to those of the hidden network layer. For each learning, Which is updated by adding it $\Delta W_{ih} = -\gamma \frac{\partial E}{\partial Wih}$. The new value becomes: $\Delta W_{ih} \leftarrow W_{ih} + \Delta W_{ih}$

Results of multilayer perceptron neural network

The objective of this study is to examine whether a PMC network can help a decision maker to correctly predict whether a decision is optimal or not by analyzing and processing the available data, information and knowledge. Table 3 provides information on the dataset used to build the ANN model.

Table 3. *Case processing summary*

		N	Percent
Sample	training	126	63,3%
	Testing	35	17,6%
	Holdout	38	19,1%
Valid		199	100,0%
Excluded		1	
Total		200	

Table 4 shows the number of neurons in each layer and the different used independent variables (26 variables). The automatic selection of the network architecture chose 4 nodes for the first hidden layer and 3 nodes for the second while the output layer had 2 nodes to code the dependent variable, i.e. an optimal decision or not. For the hidden layer, the activation function is the hyperbolic tangent while for the output layer, it is the softmax function. Then, the cross entropy is used as an error function.

Table 4. *Network information*

Input Layer	Covariates	1	Fact1-1
		2	Fact2-1
		3	Fact3-1
		4	Fact4-1
		5	Fact5-1
		6	Fact6-1
		7	Fact7-1
		8	Fact8-1
		9	Fact1-2
		10	Fact1-3

		11	Fact1-4
		12	Fact1-5
		13	Fact2-5
		14	Fact3-5
		15	Fact1-11
		16	Fac2-11
		17	Fact3-11
		18	Fact4-11
		19	Fact5-11
		20	Fact1-6
		21	Fact2-6
		22	Sex
		23	Age
		24	Education
		25	Function
		26	Experience
	Number of Units[a]		26
	Rescaling Method for covariates		Standardized
Hidden Layer(s)	Number of Hidden Layers		2
	Number of Units in Hidden Layer 1[a]		4
	Number of Units in Hidden Layer 2[a]		3
	Activation Function		Hyperbolic Tangent
Output Layer	Variables dépendantes	1	Optimal decision (max profit, min risk rationnelle..)
	Number of Units		2
	Activation Function		Softmax
	Error Function		Cross-entropy

a.- Excluding the bias unit

The SPSS network diagram is used to predict the nature of a decision (optimal or not) from 26 variables presented in the following figure (figure 1). The diagram shows two hidden layers; the first contains 4 nodes and the second 3 nodes while the activation function is hyperbolic tangent. Besides, the output layer contains two nodes then, the used activation function is the softmax function.

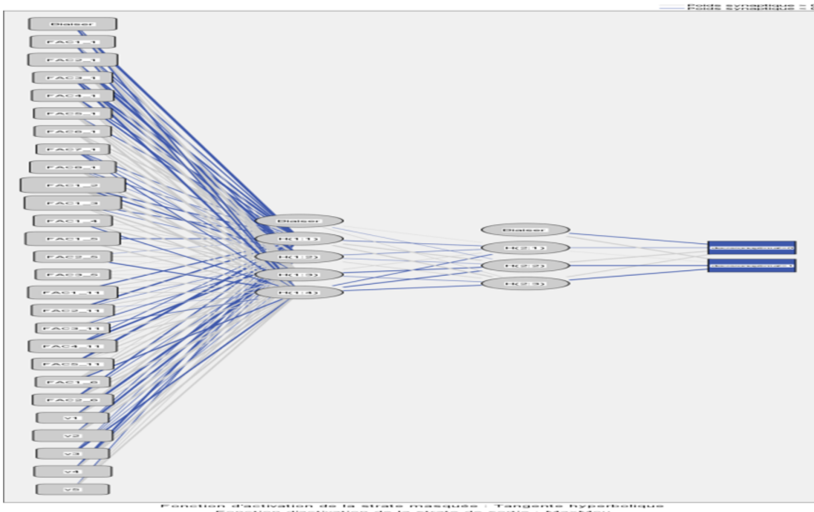

Figure 1. *Network diagram*

The model summary shown in table 5 provides information about the learning and testing results of the sample. The cross entropy error is given for the training sample and the test sample, which is the function with which the network minimizes the error during training. The low value (= 11,055) of this error indicates the power of the model to predict the type of the chosen decision. The cross-entropy error of the processed sample is larger than that of the training and testing, which means that the network model is suitable for the training data. The test sample helps prevent over-learning.

According to Table 5, the percentage of incorrect predictions for the training sample is 1.6% while for the test sample, it is 5.7% and for the processed sample, it is 15.8%. The learning procedure was carried out up to 10 consecutive steps without decreasing the error function,=which is calculated based on the test sample.

Table 5. *Model Summary*

Training	Cross Entropy Error	11,055
	Percentage of the Incorrect predictions	1,6%
	Stopping Rule Used	10 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00,05
Testing	Cross Entropy Error	10,228
	Percentage of the Incorrect predictions	5,7%
Holdout	Percentage of the Incorrect predictions	15,8%

Depedent variable: optimal decision (max profit, min. risk, rationnelle..).
a. Error computations are based on the testing sample

Table 6 shows that the synaptic weights between the peas were calculated using data from the training sample:

Table 6. *Parameter estimates*

Predictor		Predicted								
		Hidden Layer 1				Hidden Layer 2			Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(2:1)	H(2:2)	H(2:3)	[No Optimal Decision =0]	[Optimal Decision =1]
Input Layer	(Bias)	-,486	,046	,422	-,242					
	FAC1_1	-,200	-,098	,580	-,238					
	FAC2_1	-,313	-,486	,383	,259					
	FAC3_1	-,450	-,352	,448	-,366					
	FAC4_1	-,244	-,304	,240	,269					
	FAC5_1	-,209	,395	,077	,456					
	FAC6_1	,327	,016	,368	,233					
	FAC7_1	-,233	-,026	-,113	-,196					
	FAC8_1	-,210	-,018	,424	,344					
	FAC1_2	-,453	-,474	1,100	,601					
	FAC1_3	-,435	-,185	,966	,357					
	FAC1_4	,171	,263	,518	-,308					
	FAC1_5	-,737	,235	,464	,569					
	FAC2_5	-,064	,516	,047	-,665					
	FAC3_5	,072	,226	,135	,340					
	FAC1_11	-,480	,379	,392	,484					
	FAC2_11	-,562	-,093	,389	-,024					
	FAC3_11	,066	-,245	,228	-,324					
	FAC4_11	-,140	-,540	,479	,394					
	FAC5_11	-,567	,035	,286	,040					
	FAC1_6	,072	,265	,337	-,336					

	FAC2_6	-,256	-,046	,161	,416					
	v1	,331	-,470	,241	,116					
	v2	-,057	-,363	,428	,364					
	v3	-,016	-,017	-,009	-,285					
	v4	-,347	-,091	,328	,299					
	v5	-,064	,042	,052	,285					
	(Biaiser)					,035	-,021	,116		
Hidden Layer 1	H(1:1)					-,330	,629	,489		
	H(1:2)					-,276	-,139	,287		
	H(1:3)					,238	-1,481	-,243		
	H(1:4)					-,328	-,548	-,555		
	(Biaiser)								-,435	,535
Hidden Layer 2	H(2:1)								-,224	,040
	H(2:2)								1,768	-1,316
	H(2:3)								,390	-,950

Table 7 presents the classification of dependent variable (the nature of decision) according to the different partitions. For the learning process, the network correctly classified 124 responses out of 126 then, for the test sample, the network correctly classified 33 responses out of 35 while for the partition of the treated elements, the network correctly classified 32 responses out of 38. For example, for the learning process, there are 48 decisions which are expected to be non-optimal decisions and are therefore classified as non-optimal and a single decision, which is expected to be non-optimal, is classified as optimal. Likewise, regarding the nature of the optimal decisions, a planned optimal but classified not optimal single decision and planned and classified optimal 76 decisions. Overall, 98.4% of the learning sample is correctly classified. In the sample of treated elements, the sensitivity (real positive rate) is given by the following formula $\frac{TP}{TP+FN}$ 100% is 88.5%, while the specificity (real negative rate) is given by the following formula $\frac{TN}{TN+FP}$ 100%, which is equal to 75% and the model accuracy is equal to $\frac{TP+TN}{TP+FN+TN+FP}$ 100%; which gives 84.2%. On the other hand, the MLP model misclassified 6 decisions (15.8%). This error rate, which is considered low, is of great importance since the probability of predicting that a decision is optimal is classified as non-optimal or vice versa, it is minimal.

Table 7. *Classification*

Obseved Sample		Predicted		
		Non optimal Decision	Optimal Decision	correct percentage
Training	Non Optimal Decision	48	1	98,0%
	Optimal Decision	1	76	98,7%
	Overall percentage	38,9%	61,1%	98,4%
Testing	Non Optimal Decision	13	1	92,9%
	Optimal Decision	1	20	95,2%
	Overall percentage	40,0%	60,0%	94,3%
Holdout	Non Optimal Decision	9	3	75,0%
	Optimal Decision	3	23	88,5%
	Overall percentage	31,6%	68,4%	84,2%

Dependent Variable: optimal decision (max profit, min. risk , rationnelle,..)

These results are verified in the figure below which shows graphs in box of predicted pseudo-probabilities. For the result of the trajectory-dependent variable, the graph displays box diagrams that classify the predicted pseudo-probabilities based on the dataset. For each case, the probability greater than 0.5 indicates a correct prediction.

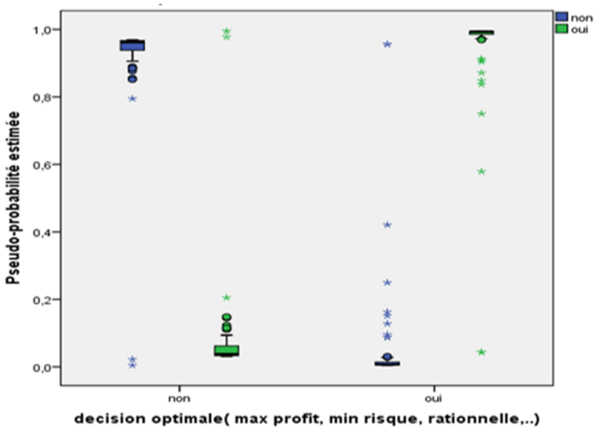

Figure 2. *Predicted-by- observed-chart*

Starting from the left, blox plot shows the predicted probability that an observed non-optimal decision is in the non-optimal category. The second blox plot shows the probability for a decision to be classified in the non-optimal category when it is in the optimal one. The third blox plot shows that in an optimal observed decision, the expected probability is not optimal. The right blox plot shows the probability that a really optimal decision is classified in the optimal category.

Then, the ROC curve is a diagram of the sensitivity versus specificity, which shows the performance of the classification for all possible thresholds. Figure 9 shows the sensitivity and specificity graph (= 1- false positive rate), based on the combined learning and testing samples. The 45-degree diagonal line from the upper right corner of the graph to the lower left corner represents the scenario of guessing the class at random. The further the curve moves away from the baseline by 45 degrees, the more precise the classification is.

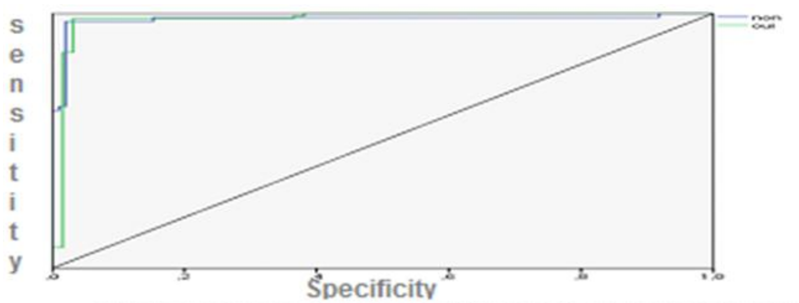

Figure 3. *ROC curve*

Figure 3 gives the area under the ROC curve, the value of which shows that if a decision of the optimal decision category and a decision of the non-optimal decision category are chosen at random, there is a probability of 0.976 that the pseudo-probability predicted by the model for the first decision will be in the optimal decision category, or higher than the pseudo-probability predicted by the model for the second decision to be in the optimal decision category.

The graph in figure 4 gives the cumulative gains, i.e. the presence of correct classifications obtained by the MLP model compared to the correct classifications which can result from chance (i.e. without using the model). For example, the third point on the curve for the non-optimal decision category is (30%, 78%), which means that if the network marks a set of data and sorts all the cases according to the expected non optimal pseudo-decision probability. The top 30% is expected to contain approximately 75% of all cases that actually take the non-optimal decision category.

Table 8. *Area under the curve*

		Area
optimal decision (max profit, min risque, rationnelle..)	Non optimal Decision	,976
	Optimal Decision	,976

Selecting 100% of the data set makes it possible to obtain all the observed cases or the decision is not optimal the gain is a measure of the effectiveness of a classification model calculated as the percentage of correct predictions obtained with the model, compared to the percentage of correct predictions obtained without a model (reference base) the higher the curve is above the baseline, the greater the gain. A higher overall gain indicates better performance.

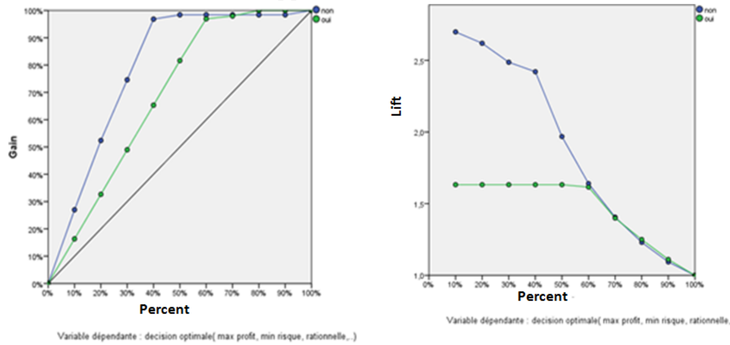

Figure 4. *Cumulative gains and lift chart*

The elevation diagram, as well as the gain diagrams, are visual aids to assess the performance of classification models. However, the confusion matrix evaluates the performance of the model on the part of the population. A lift card uses part of the data set to give a clear view of the advantages of using a model over the absence of aother. The values of the gain diagram are used to calculate the lifting factor (i.e. the profit): the lifting at 78% for the non-optimal decision category is 75% / 30% = 2.5. Figure 6 shows the impact of each independent variable in the ANN model in terms of relative and normalized importance. It also illustrates the importance of the variables, that is, the sensitivity of the model is the change of each variable.

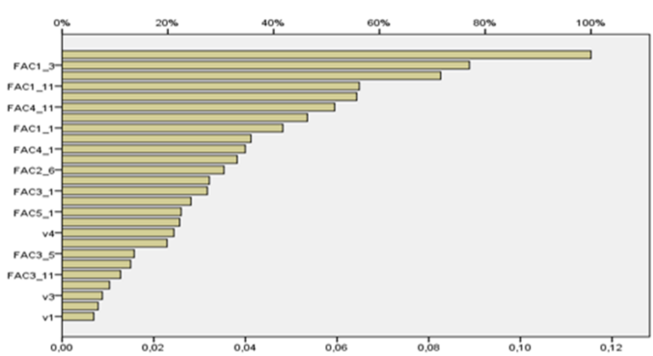

Figure 5. *Independent variable importance chart*

Table 9. *The importance of the Independent variables*

	Importance	standarized Importance
Fact1-1	,048	41,8%
Fact2-1	,064	55,7%
Fact3-1	,032	27,5%
Fact4-1	,040	34,6%
Fact5-1	,026	22,5%
Fact6-1	,023	19,8%
Fact7-1	,010	9,0%
Fact8-1	,054	46,4%
Fact1-2	,115	100,0%
Fact1-3	,089	77,0%
Fact1-4	,028	24,4%
Fact1-5	,083	71,6%
Fact2-5	,026	22,2%
Fact3-5	,016	13,6%
Fact1-11	,065	56,2%
Fac2-11	,041	35,7%
Fact3-11	,013	11,0%
Fact4-11	,059	51,5%
Fact5-11	,038	33,1%
Fact1-6	,015	13,0%
Fact2-6	,035	30,6%
Sexe	,007	6,0%
Age	,032	27,8%
Education	,009	7,6%
Fonction	,024	21,1%
Experience	,008	6,8%

The graph shows that the variables linked to fact1-2, fact1-3, fact1-5, fact1-11 and fact 4-11 have the greatest effect on the way the network has classified the nature of decision. Similarly, fact 1-1, fact 8-1, fact 4-1, fact 5-11, fact 2-11 and fact 2-6 are also major determinants of the predictive power of the model besides, they are much more important than the other variables (v4, v1, fact7-1, fact2 -5,).

Conclusion

The objective of this research is to determine the effectiveness of artificial neuron networks in predicting the nature of decisions, based on data collected from a questionnaire sent by email or directly sent to the company. The literature review showed that the neural networks outperformed all other classifiers in terms of forecasting accuracy. A multilayer perceptron neural network was formed through a back propagation algorithm, in order to predict the nature of a decision. In fact, the classification accuracy rate was very high with 84.2% in the classification of decisions in the optimal decision category and expected non-optimal decision. The results showed that the variables fact1-3, fact1-2 and fact1-5 have the greatest contribution in the network construction. These variables are essentially related to the processes of knowledge and information, which are at the heart of economic intelligence and knowledge management processes. In conclusion, the factors related to the process of economic intelligence and knowledge management have a strong relationship with the prediction of decisions. Moreover, there is strong evidence that the proposed model can be effectively used to predict the nature of a decision made within a company and help the decision maker to collect, process and analyze information so as to increase the chance of choosing an optimal decision through profit maximization and minimization, which are suitable for business needs. However, our approach can be improved in the economic and financial sector, in particular, to forecastthe performance of a company and improve it by applying other learning algorithms.

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