Demystifying inflation dynamics in Rwanda: an ARMA approach

NYONI, THABANI

University of Zimbabwe

7 May 2019

Demystifying Inflation Dynamics in Rwanda: An ARMA Approach

Nyoni, Thabani

Department of Economics

University of Zimbabwe

Harare, Zimbabwe

Email: nyonithabani35@gmail.com

ABSTRACT

This research uses annual time series data on inflation rates in Rwanda from 1967 to 2017, to model and forecast inflation over the next decade using ARMA models. Diagnostic tests indicate that W is I(0). The study presents the ARMA (3, 0, 0) model [which is nothing but an AR (3) model]. The diagnostic tests further imply that the presented optimal ARMA (3, 0, 0) model is stable and acceptable. The results of the study apparently show that W will be approximately 7.45% by 2020. Policy makers and the business community in Rwanda are expected to take advantage of the anticipated stable inflation rates over the next decade.

Key Words: Forecasting, Inflation, Rwanda

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation is the sustained increase in the general level of prices and services over time (Blanchard, 2000). The negative effects of inflation are widely recognized (Fenira, 2014). An increase in the general price level causes a reduction in the purchasing power of money. Inflation reflects a reduction in the purchasing power per unit of money – a loss o real value in the medium of exchange and unit of account within the economy (Walgenbach *et al*, 1973). Inflation exerts a constraining effect on the key drivers of growth. The price increase reduces consumption and therefore production and employment. It exerts an inhibitory effect on investment, due to the rise of the nominal wages and the prices of raw materials, both in local and foreign currency. Inflation also contributes to the deterioration of the trade balance when the prices of domestic goods and services rise more than those of foreign competitors. To this are added its negative effects on social activity because of the deterioration of the purchasing power (Fenira, 2014). Furthermore, price instability can generally jeopardize the macroeconomic stability (Bonato, 1998).

Price stability is a prime objective for monetary authorities in most economies and monetary unions around the world (King, 2005). It is now generally accepted that keeping low and stable rates of inflation is the primary objective of central banks (Hector & Valle, 2002). To prevent the aforementioned undesirable outcomes of price instability, central banks require proper understanding of the future path of inflation to anchor expectations and ensure policy credibility; the key aspects of an effective monetary policy transmission mechanism (King, 2005). Inflation forecasts and projections are also often at the heart of economic policy decision-making, as is the case for monetary policy, which in most industrialized economies is mandated to maintain price stability over the medium term (Buelens, 2012). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012).

Like most central banks around the world, the primary objective of monetary policy in Rwanda is to keep inflation low and stable and therefore support the government's macroeconomic policies aimed at promoting economic growth (Gichondo *et al*, 2018). In Rwanda, National Bank of Rwanda (BNR) initiated the modeling and forecasting function in 2009 with the objective of feeding the monetary policy process with evidence based information. The need was strengthened with the defiance of the prevailing monetary targeting framework, stressing the importance of developing modeling and forecasting capacity as the economy moves into interest-rate-based framework. Currently, the BNR has adopted and adapted several modeling and forecasting tools. For near-term forecasting, economists at BNR use Autoregressive Moving Average (ARMA), Vector Autoregressive (VARs and BVARs) and State-Space models. For medium term forecasting, BNR has adapted the Forecasting and Policy Analysis System (FPAS) and developed its own (in-house) core model of inflation (CMI) (Mwenese & Kwizera, 2018). This study seeks to model and forecast annual rates of inflation in Rwanda based on ARMA models.

RELATED PREVIOUS STUDIES

Stovicek (2007) forecasted inflation in Slovenia using ARMA models with a data set ranging from January 1994 to June 2006 and revealed that in terms of forecast ability ARMA models outperform AR models, when allowing for the same degrees of freedom. Osarumwense & Waziri (2013) modeled monthly inflation rate volatility using GARCH models with a data set ranging over the period January 1995 to December 2011 and found out that the GARCH (1, 0) + ARMA (1, 0) model is appropriate for forecasting inflation in Nigeria. Popoola *et al* (2017) modeled and forecasted inflation rate in Nigeria using Box-Jenkins ARIMA models with a data set ranging over the period January 2006 to December 2015 and established that the ARIMA (0, 1, 1) model was the best model for forecasting inflation rate in Nigeria. Nyoni (2018) analyzed inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni also (2018) modeled and forecasted inflation in Kenya using ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; analyzed inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria. In the case of Rwanda, Habimana *et al* (2016), modeled and forecasted consumer price index (*a measure of inflation*) using Box-Jenkins ARIMA models and established that the ARIMA (4, 1, 6) model was the optimal model for forecasting inflation in Rwanda.

MATERIALS & METHODS

ARMA Models

For the purpose of forecasting rates of inflation in Rwanda, ARMA models were specified and estimated. A general ARMA (p, q) model is specified as follows:

$$W_t = \alpha_1 W_{t-1} + \alpha_2 W_{t-2} + \cdots + \alpha_p W_{t-p} + \varepsilon_t + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-2} + \cdots + \beta_q \varepsilon_{t-q} \dots\dots\dots\dots\dots.. [1]$$

Where:

W_t rates of inflation in Rwanda at time t;

ε_t is the error term at time t;

$\varepsilon_{t-1} \dots\dots\dots\dots. \varepsilon_{t-q}$ are past errors;

$W_{t-1} \dots\dots\dots\dots. W_{t-p}$ are past rates of inflation in Rwanda;

$\alpha_1 \dots\dots\dots\dots. \alpha_p$ and $\beta_1 \dots\dots\dots\dots. \beta_q$ are estimation parameters.

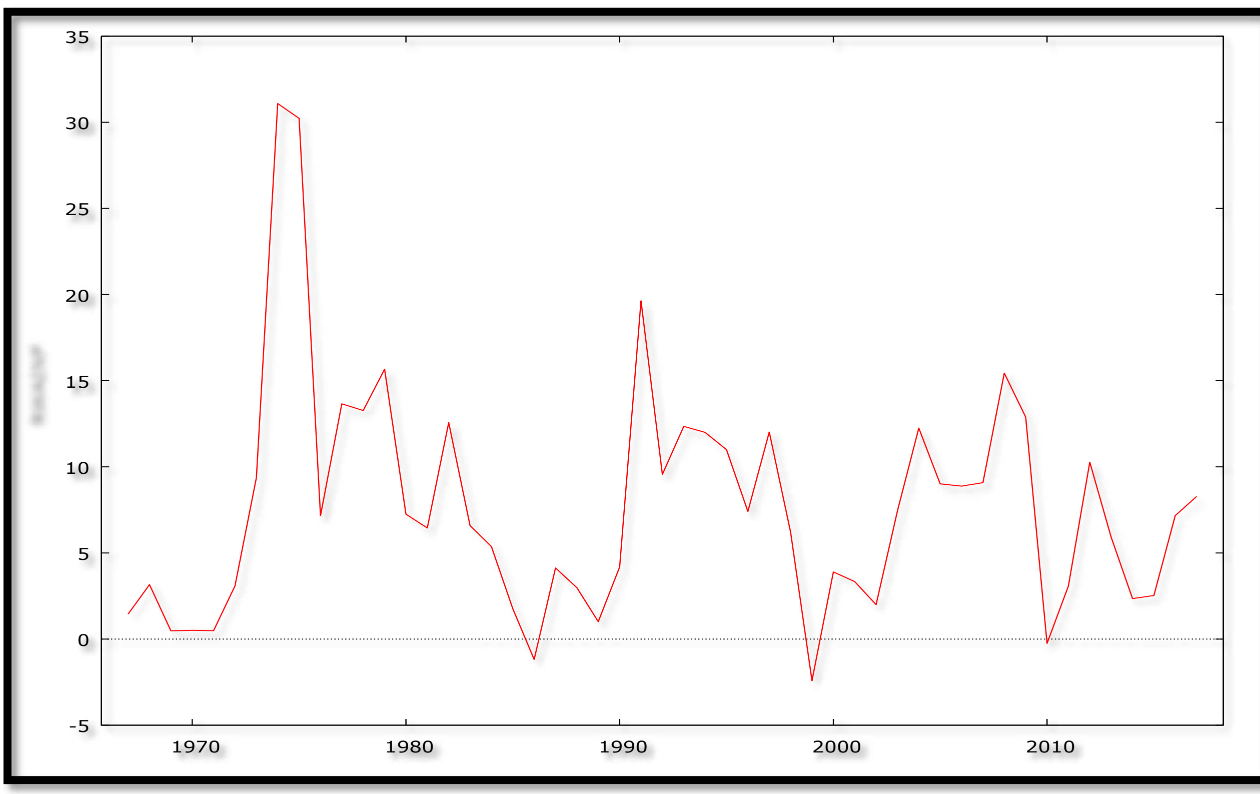
Data Collection

This study is based on a data set of annual rates of inflation in Rwanda (RWAINF or simply W) ranging over the period 1967 – 2017. All the data was gathered from the World Bank.

Diagnostic Tests & Model Evaluation

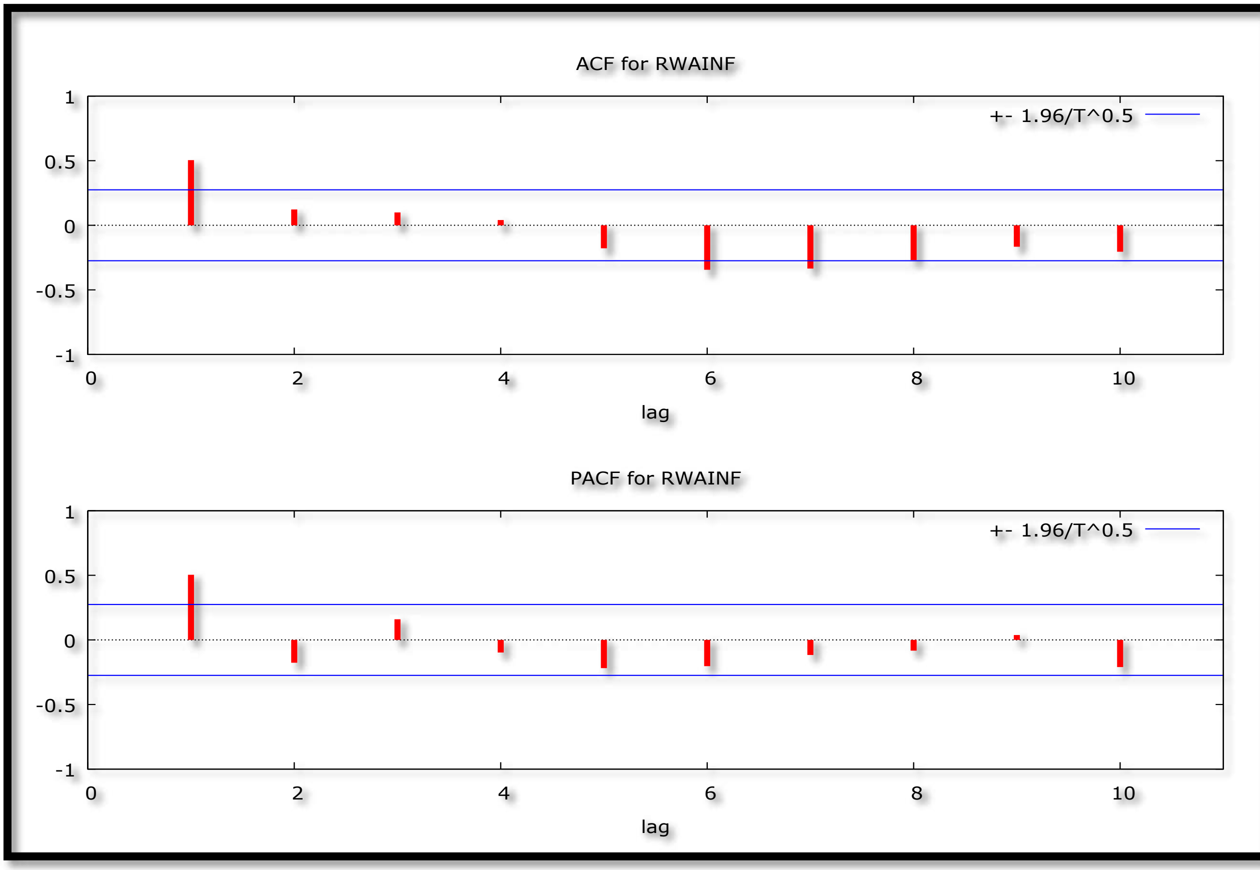
Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Figure 2



The ADF Test

Table 1: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-4.023454	0.0028	-3.568308	@1%	Stationary
			-2.921175	@5%	Stationary
			-2.598551	@10%	Stationary

Table 2: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-4.032371	0.0137	-4.152511	@1%	Not stationary
			-3.502373	@5%	Stationary
			-3.180699	@10%	Stationary

Table 3: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
W	-2.345142	0.0198	-2.612033	@1%	Not stationary
			-1.947520	@5%	Stationary

		-1.612650	@10%	Stationary

Figures 1 and 2 and tables 1 – 3 show that W is an I (0) variable.

Evaluation of ARMA models (with a constant)

Table 4

Model	U	ME	RMSE	MAPE
ARMA (1, 0, 1)	0.79939	0.032182	5.6597	200.7
ARMA (2, 0, 2)	0.74382	0.045204	5.6524	197.54
ARMA (1, 0, 0)	0.73849	0.060471	5.8137	207.82
ARMA (2, 0, 0)	0.82524	0.025267	5.7247	208.98
ARMA (3, 0, 0)	**0.69952**	0.071956	5.64	193.67
ARMA (0, 0, 1)	0.85412	0.024105	5.6624	201
ARMA (0, 0, 2)	0.81797	0.029192	5.6624	201.47
ARMA (0, 0, 3)	0.79551	0.032069	5.6608	200.4
ARMA (4, 0, 0)	0.72882	0.036832	5.6161	195.24
ARMA (1, 0, 2)	0.75649	0.042823	5.6535	198.29
ARMA (1, 0, 3)	0.7239	0.049156	5.6503	196.17
ARMA (2, 0, 1)	0.76545	0.037983	5.6561	198.96
ARMA (3, 0, 1)	0.70423	0.063407	5.6322	193.62

Theil’s U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018). The study will consider the Theil’s U in order to choose the best model for forecasting inflation rates in Rwanda. Therefore, the ARMA (3, 0, 0) model is carefully selected.

Residual & Stability Tests

ADF Tests of the Residuals of the ARMA (3, 0, 0) Model

Table 5: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.702149	0.0000	-3.577723	@1%	Stationary
			-2.925169	@5%	Stationary
			-2.600658	@10%	Stationary

Table 6: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.835202	0.0000	-4.165756	@1%	Stationary
			-3.508508	@5%	Stationary
			-3.184230	@10%	Stationary

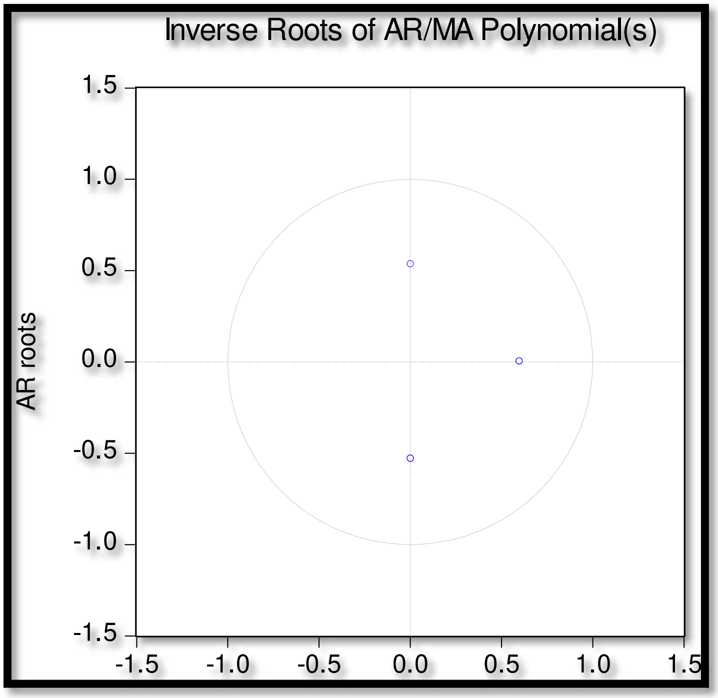
Table 7: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.775727	0.0000	-2.615093	@1%	Stationary
			-1.947975	@5%	Stationary
			-1.612408	@10%	Stationary

Tables 5, 6 and 7 demonstrate that the residuals of the ARMA (3, 0, 0) model are stationary.

Stability Test of the ARMA (3, 0, 0) Model

Figure 3



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARMA (3, 0, 0) model is indeed stable.

FINDINGS

Descriptive Statistics

Table 8

Description	Statistic
Mean	7.6888
Median	7.17
Minimum	-2.41
Maximum	31.09
Standard deviation	6.8
Skewness	1.6454
Excess kurtosis	3.0118

As shown above, the mean is positive, i.e. 7.6888%. The minimum is -2.41% and the maximum is 31.09%. The skewness is 1.6454 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis, as noted by Nyoni & Bonga (2017) should be around 3 for normally distributed variables and in this study kurtosis has been found to be 3.0118; implying that the inflation series is normally distributed.

Results Presentation[1]

Table 9

ARMA (3, 0, 0) Model: $W_t = 7.51325 + 0.623085W_{t-1} - 0.271943W_{t-2} + 0.168824W_{t-3} \ldots\ldots\ldots [2]$ P: (0.0000) (0.0000) (0.0877) (0.2241) S. E: (1.58147) (0.138315) (0.159229) (0.138877)				
Variable	Coefficient	Standard Error	z	p-value
Constant	7.51325	1.58147	4.751	0.0000***
AR (1)	0.623085	0.138315	4.505	0.0000***
AR (2)	-0.271943	0.159229	-1.708	0.0877*
AR (3)	0.168824	0.138877	1.216	0.2241

Predicted Annual Inflation

Table 10

Year	Prediction	Std. Error	95% Confidence Interval
2018	7.24	5.619	-3.77 - 18.26
2019	7.08	6.621	-5.90 - 20.05
2020	7.45	6.653	-5.59 - 20.48
2021	7.54	6.665	-5.52 - 20.61
2022	7.48	6.698	-5.65 - 20.61
2023	7.47	6.711	-5.68 - 20.62
2024	7.50	6.713	-5.65 - 20.66
2025	7.51	6.713	-5.65 - 20.67
2026	7.51	6.714	-5.65 - 20.67
2027	7.51	6.714	-5.65 - 20.67

Table 10, with a forecast range of 10 years clearly shows that inflation rates in Rwanda will not exceed 8% within the next 10 years, ceteris paribus. With a 95% confidence interval of -5.59% to 20.8% and a predicted annual inflation rate of 7.45% by 2020, the chosen ARMA (3, 0, 0) model indicates that there will be price stability in Rwanda in 2020.

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

CONCLUSION

Accurate forecasting is useful for effective policy planning (Jesmy, 2010). The main aim of this study was to select the optimal ARMA model for modeling and forecasting inflation in Rwanda and the optimal model was selected based model identification statistics shown in table 4 above. As already shown, the optimal model is the ARMA (3, 0, 0) model and this model is envisaged to serve as an early warning signal to Rwandan policy makers, business leaders, investors and employers to prepare themselves and to make the right move to calculate the strength of the anticipated new environment and to take feasible necessary action in their business activities.

REFERENCES

[1] Blanchard, O (2000). Macroeconomics, 2nd Edition, *Prentice Hall*, New York.

[2] Bonato, L (1998). The Benefits of Price Stability: Some Estimates from New Zealand, *Reserve Bank of New Zealand Bulletin*, 61 (3).

[3] Buelens, C (2012). Inflation modeling and the crisis: assessing the impact on the performance of different forecasting models and methods, *European Commission*, Economic Paper No. 451.

[4] Fenira, M (2014). Democracy: a determinant factor in reducing inflation, *International Journal of Economics and Financial Issues*, 4 (2): 363 – 375.

[5] Gichondo, A., Karangwa, M., Kasai, N & Munyakindi, P (2018). Optimal inflation for economic growth in Rwanda, *BNR Review*, 13: 28 – 43.

[6] Habimana, N., Wanjoya, A & Waititu, A (2016). Modeling and Forecasting Consumer Price Index (Case of Rwanda), *American Journal of Theoretical and Applied Statistics*, 5 (3): 101 – 107.

[7] Hector, A & Valle, S (2002). Inflation forecasts with ARIMA and Vector Autoregressive models in Guatemala, *Economic Research Department*, Banco de Guatemala.

[8] Jesmy, A (2010). Estimation of future inflation in Sri Lanka using ARMA model, *Kalam Journal*, V: 21 – 27.

[9] King, M (2005). Monetary Policy: Practice Ahead of Theory, *Bank of England*.

[10] Mwenese, B & Kwizera, A. P (2018). Modeling and forecasting inflation dynamics in Rwanda, *BNR Review*, 13: 45 – 71.

[11] Nyoni, T & Nathaniel, S. P (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 91351.

[12] Nyoni, T (2018). Modeling and Forecasting Inflation in Zimbabwe: a Generalized Autoregressive Conditionally Heteroskedastic (GARCH) approach, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88132.

[13] Nyoni, T (2018). Modeling Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.

[14] Nyoni, T (2018). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6): 16 – 40.

[15] Nyoni, T & Bonga, W. G (2017). Population Growth in Zimbabwe: A Threat to Economic Development? *DRJ – Journal of Economics and Finance*, 2 (6): 26 – 39.

[16] Osarumwense, O. I & Waziri, E. I (2013). Modeling monthly inflation rate volatility, using Generalized Autoregressive Conditionally Heteroskedastic (GARCH) models: evidence from Nigeria, *Australian Journal of Basic and Applied Sciences*, 7 (7): 991 – 998.

[17] Popoola, O. P., Ayanrinde, A. W., Rafiu, A. A & Odusina, M. T (2017). Time series analysis to model and forecast inflation rate in Nigeria, *Anale. Seria. Informatica.*, XV (1): 174 – 178.

[18] Stovicek, K (2007). Forecasting with ARMA models: The case of Slovenia inflation, *Bank of Slovenia*, pp: 23 – 56.

[19] Walgenbach, P. H., Dittrich, N. E & Hunson, E. I (1973). Financial Accounting, *Harcout Brace Javonvich*, New York.