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Dynamic Behaviour and Drivers of the Kwacha-US Dollar Exchange Rate During Droughts

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Abstract

The objective of this paper is to establish the dynamic behaviour and the underlying factors that cause the Kwacha (ZMW) to depreciate against the US dollar (USD) during drought periods. A Bayesian with sign restrictions estimation method is used to generate impulse response functions from a vector autoregressive model in order to understand the dynamic behaviour of the exchange rate under a drought shock. A historical decomposition method is also used to establish the shocks that account for the depreciation of the exchange rate. The results suggest that foreign exchange demand increases during drought episodes and thereby contribute to the currency depreciation. The increase in foreign exchange demand coincides with a rise in foreign currency deposit liabilities in commercial banks alongside the increase in the banks' net foreign assets. This may suggest a tendency by economic agents to hold more foreign currency in drought periods as a precautionary measure. Global shocks captured by copper price decline augments depreciation, including during episodes of drought. Therefore, actions that limit demand for foreign currency, such as, excess liquidity draining operations may help to minimise foreign exchange demand during drought times and help moderate exchange rate depreciation.

Key words: Exchange rate depreciation, Zambia, Drought, Bayesian VAR, Sign restrictions, Historical decomposition

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1.0 Introduction

The exchange rate is a very important variable to economic agents as its dynamics have a bearing on international trade, financial flows, and inflation. A depreciation of the exchange rate, for example, leads to an increase in the amount of the local currency needed to transfer a fixed amount of foreign currency to another country. A depreciation of the local currency may also cause prices for imported items to rise, assuming foreign inflation is stable, thereby feeding adversely into the domestic inflationary process. Equally, local currency depreciation may lead to a reduction in imports if deemed expensive by resident economic agents. However, a depreciation on the other hand may result into exports becoming competitive as non-residents will find locally produced goods and services relatively cheap. This may result into favourable net external demand for the country with positive implications on the country's trade balance and ultimately the current account. The possibility of different outcomes in the exchange rate requires that factors – economic, social and nature based - that may cause the exchange rate to move are investigated to help with optimal policy interventions.

The primary objective of this paper is to explore the dynamic behaviour and underlying factors behind the Zambian Kwacha/US Dollar exchange rate during episodes of droughts experienced in Zambia. Since various forms of drought have been identified, this paper considers the meteorological drought, which, in the words of Hume (1995) is taken as "a reduction in rainfall supply compared with a specified average condition over some specified period."

Anecdotal evidence suggests that during periods of drought in Zambia, the exchange rate largely tends to depreciate[2], disregarding other factors at play. Although the rate of depreciation appears to be relatively small in some drought instances, but going by the way economic and financial variables interact as a system (Kirman, 2017; Farmer, 2012; and Foster, 2006), the exchange rate interaction with other variables may not be linear and thus its effect on other variables may not be relatively small. Small changes may lead to amplified outcomes on other variables in the system as argued by Schasfoort (2017), Kirman (2006), and Kirman (2016) on the behaviour of dynamic complex systems. In addition, the effect of the exchange rate shock on other variables may lag in the physical space (time) since a shock to an economic or financial variable affects other variables within the system much more with a lag (Asghar and Hussain, 2019) and the effect of the shock can be very persistent (Curran and Velic, 2019; Fuhrer, 2010; and Cashin, Liang and Mcdermott, 2000). This implies that small changes in economic and financial variables may not be trivial due to the feedback mechanism as well as transference and persistence of shocks. The interaction of economic variables in a system is influenced by a memory function that links them (Tarasov and Tarasova, 2018) and an economy being a complex system, there is a possibility of the effects of natural occurrences transferred to economic variables, including the exchange rate. Therefore, in the context of the exchange rate, there is then need to understand its dynamic behaviour owing to a drought shock in the system as well as establish other underlying

[2] see Figure 1

factors. This is to help understand the propagation of its impulses over time for possible policy actions aimed at supporting the economic system to attain or stay in a steady state.

A number of studies have been undertaken on the exchange rate in Zambia but none has focused on the impact of drought on the exchange rate in the context of historical decompositions and or dynamic behaviour. However, Roger, Smith and Morrissey (2017) undertook a historical decomposition of shocks to the exchange rate but not involving a drought shock. It has also explored the dynamic behaviour of the exchange rate but in the context of shocks due to macroeconomic and financial impulses. This study extends their work by focusing on the dynamic behaviour and possible drivers of the exchange rate under a drought shock. Further, this study digresses from the study by Roger, Smith and Morrissey (2017) as it utilises a unique data set on foreign exchange sales and purchases found in the Bank of Zambia (BoZ) database. It thus focuses on the shocks to foreign exchange demand and supply in explaining exchange rate dynamics in drought periods. Roger, Smith and Morrissey (2017) sought to understand how shocks to money supply, output gap, inflation and the Federal funds rate affect the ZMW/USD exchange rate. The approach adopted in the current study, therefore, offers another unique contribution to the literature on the subject of exchange rate in Zambia.

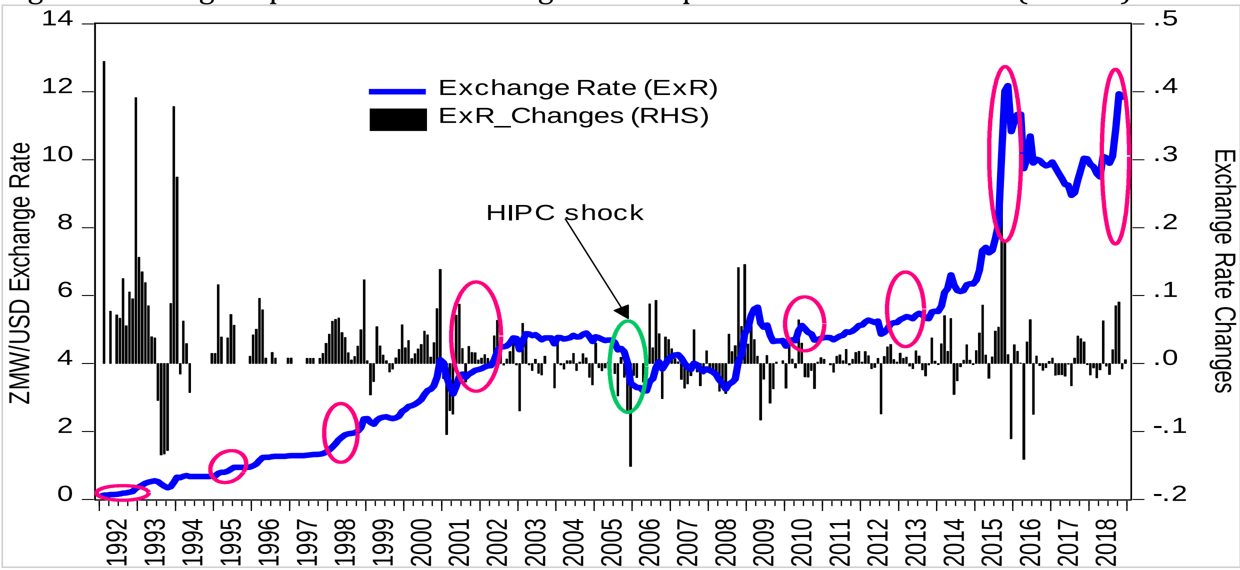
Other studies specifically focusing on Zambia's exchange rate have been undertaken in the recent past to address various research questions credited to Chipili (2016); Zgambo (2015); Chipili (2014); Chipili (2013a); Chipili (2013b); Pamu, Musongole and Chokwe (2012); and Chipili (2012). None of these studies, however, has looked at the behaviour of the exchange rate in the context of drought in Zambia. Even then, none of these studies have also explored the dynamic behaviour of the exchange rate depreciation observed during episodes of drought in Zambia.

The rest of the paper is structured as follows: Section 2 contains information on the coincidences between drought periods and exchange rate depreciation. Section 3 provides a brief survey of the relevant literature. Section 4 outlines the empirical models, methodology. In section 5, there is data description. Section 6 presents the results and discussion. Section 7 concludes and provides policy recommendations along side areas requiring further research.

2.0 Drought Episodes and Exchange Rate Depreciations in Zambia

Periods of drought in Zambia tend to be accompanied by exchange rate depreciation (Figure 1). For instance, during the 1992 drought, the exchange rate depreciated as some monthly changes during the period were higher than monthly changes in the following year. Similarly, in 1995, the drought episode coincided with exchange rate depreciation as positive changes (depreciation) were higher than those observed in the neighbourhood of the year 1995. The only drought period in which the exchange rate appreciated was 2005. However, this was largely due to the shock arising from attaining the Highly Indebted Poor Countries (HIPC) Initiative Completion Point and copper price recovery that augmented foreign exchange supply in the economy.

Figure 1: Drought Episodes and Exchange Rate Depreciation Coincidences (circled)



However, in 2015 and 2018, drought episodes that also coincided with copper price declines following adverse commodity price shocks owing to Fed monetary policy normalization and US-China trade war, exchange rate depreciation was relatively more amplified during the two periods.

3.0 Review of Literature

Popular theories on exchange rate determination assume equilibrium of markets in the domestic and international economy. This class of theories include the purchasing power parity (PPP) which assumes equilibrium in the goods market, the monetary theory which assumes equilibrium in the money markets and the asset theory (portfolio balancing) which assumes equilibrium in the asset markets. Of course, there exists other variants. For a comprehensive list of such see Mussa (1984), Visser (2004) and, Vo and Vo (2022) for example.

Existing theoretical ideas on the exchange rate determination or dynamics do not expressly show the role of climate change in the behaviour of exchange rates. Most likely, this is because climate change has just been realised as a potential threat, not just physical elements, but also economic and financial variables. However, frameworks being developed in the context of the physical and transitional risks associated with climate change can provide some insights into modelling the effects of climate change on economic and financial variables. Some efforts done this far to postulate the interaction between macro-financial and climate related risks include a detailed conceptual framework by Feyen, Utz and Huertas (2020). This highlights the possible channels through which climate change-based risk impulses can affect real, monetary, financial, external and fiscal sectors' related variables. Market prices are also included. In the framework, internally and externally induced physical and transition risks associated with climate change are mapped to macro-financial variables.

It is a remarkable effort, in view of the complexity of climate change in terms of the effects, that has attempted to formalise the relationship between climate change and macro-finance variables and could be a good guide to economic modelling of climate change related risks. It substantially departs from the framework suggested by Freire-González, Decker and Hall (2017). The latter, however, focus only on one element of the physical risks of climate change, water scarcity. The earlier framework by Benson and Clay (1998) can still be an alternative guide for empirical work on drought related shocks impact on economic variables. It outlines a comprehensive number of channels through, which drought related impulses can be transmitted to economic and financial variables.

Ogun (2012) provided a model for the determination of the exchange rate for a developing country operating a flexible exchange that includes a proxy for weather condition in the domestic economy, and therefore climate change effects, taken as a cyclical variable reflecting the difference between actual and trend real agricultural output.

The effects or implications of drought or climate variability on economic variables have been studied by Mbao (2019), Edwards, Gray and Hunter (2019), Kilimani et al. (2018), Freire-González, Decker and Hall (2017), Juana et al. (2014), Kamber, McDonald and Price (2013), and Benson and Clay (1998). While Kamber, McDonald and Price (2013) explored the effect of the interaction between the exchange rate and indicators of drought conditions, the other studies focused mainly on the effects of drought on real variables. Despite Kamber, McDonald and Price (2013) undertaking empirical work in which the exchange rate interacted with indicators that capture drought incidences, they nonetheless did not explore the dynamic behaviour of the exchange rate in drought periods. The current study is, therefore, unique in that sense. However, this uniqueness also comes with challenges especially related to methodological issues as there may be no sufficient studies to learn from in addressing the problem at hand. This notwithstanding, one may treat the challenge at hand as a historical decomposition problem or as one that requires sign restrictions in a VAR framework for generating impulse responses as for instance done by Kamber, McDonald and Price (2013) using New Zealand data.

On treating the estimation challenge as the historical decomposition, one will seek to decompose the shocks associated with the variable of interest and trace the contributions from the associated variables used in the estimation framework. This is because fluctuations to a variable of interest are caused by shocks to related variables. For example, in the context of the problem at hand, fluctuations to the exchange rate may likely arise from shocks to foreign exchange demand and supply, global shocks and other factors that have influence on the exchange rate. The historical decomposition estimation procedure is standard within the VAR framework and it does provide an interpretation of historical fluctuations of a given time series by identifying its structural shocks (Wong, 2017). This tool is also important because a VAR in its treament of variables as being endogenous allows for feedback mechanism that may exist among variables to be taken into account during the estimations (Ghoshray and Pundit, 2020).

Historical decomposition is an innovation accounting that has gained popularity in empirical work and include Roger, Smith and Morrissey (2017), Wong (2017), Fackler and McMillin (1998), Fackler and Parker (1994) and Burbidge and Harrison (1985) done for various reasons. For example, Roger, Smith and Morrissey (2017) analysed the ZMW/USD exchange rate shocks using historical decomposition within the Bayesian VAR framework although the focus was not on establishing the behaviour of the exchange rate under drought conditions. The study explored the use of both sign and zero restrictions, within the context of the structural Bayesian VAR to generate dynamic impulse responses for the exchange rate of the Kwacha/US dollar following some shocks. Like stated before, this did not include any variable that may capture conditions of drought. However, it is important to state that the study by Kamber, McDonald and Price (2013) is somewhat similar to this study from the estimation perspective. This is due to the use of zero restrictions on some contemporaneous variables. Although the latter also used Bayesian techniques, what is of utility to the current study is the incorporation of the drought indicator variable in the VAR system to establish the impact of drought on the trade weighted exchange rate index (TWI) for New Zealand.

The study on New Zealand shows the dollar TWI to have largely been unchanged following the 2013 drought over the first half of 2013. The authors attribute this to the rise in global milk prices arising from the global supply disruption due to drought in New Zealand since it is one of the major exporters of milk. However, the estimates predicted a depreciation of the currency in the early part of 2014. This may be suggesting that the horizon for impulse responses should cover more than one year to fully capture the dynamic impact since shocks from one variable may affect others much more with a lag.

Sign restrictions in identifying the transmission and impact of shocks within a structural VAR framework estimated with Bayesian techniques have proliferated in literature following earlier works by Dwyer (1998), Faust (1998) and Canova and Nicoló (2002). Uhlig (2005) and Peersman (2005) are among the first to use Bayesian methods with sign restrictions in empirical set-up. However, subsequent studies have argued that it is not enough just to use sign restrictions. These should be accompanied by zero restrictions if meaningful impulse response functions consistent with economic theory have to be estimated. The zero restrictions have to be imposed on parameters that have a contemporaneous impact from the shock. For example Baumeister and Hamilton (2019), Arias et al. (2018), Kabashi and Suleva (2016), Baumeister and Hamilton (2015) and Kilian and Murphy (2012) have used both zero and sign restrictions to addresss their respective research questions. Baumeister and Hamilton (2019 and 2015) introduce a mechanism where one who is doing applied research does not need to apply a recursive ordering of endogenous variables for the purpose of shock identification in a VAR set-up. They have used this approach to identify the oil demand and supply shocks. Using the same modelling approach, Patnaik (2022) was able to identify the COVID-19 shock's impact on India's macroeconomic variables. This demonstrates the effectiveness of the tool although the concern is whether it is ideal for shocks that may not have a contemporeneous effect on some parameters as the case may be with a drought shock which is only noticed after some passage of time.

The sign restriction approach is such that the estimated impulse responses are allowed to interact with the sign restriction based on the Givens rotation matrix, as for example in the context of Uhlig (2005) who in his case employed the normal-Wishart prior to create candidate structural shocks (Fry & Pagan, 2011). Traditionally, the Cholesky decomposition has been used in the identification and recovery of shocks in a VAR set-up since the pioneering works of Sims (1980). The Cholesky decomposition can be used for short or long-run restrictions to recover the structural shocks consistent with Bernanke (1986) and Blanchard and Quah (1989). Nonetheless, these classical methods are not consistent with standard DSGE models and thus the sign restriction way to identification of structural shocks has been developed (Danne, 2015).

In light of the empirical work by Roger, Smith and Morrissey (2017) on Zambia, this study extends their work by focusing on the determination of the shocks causing exchange rate depreciation in a drought period, something that has not be done before. It also differs from their study by utilising a unique data set on foreign exchange sales and purchases found in the Bank of Zambia (BoZ) database. It thus focuses on the shocks to the foreign exchange demand and supply in explaining exchange rate dynamics during drought periods. Roger, Smith and Morrissey (2017) sought an understanding of how shocks to money supply, output gap, inflation and Feds fund rate affects the ZMW/USD exchange rate. The approach adopted in the current study, therefore, offer another unique dimension to the literature on the subject of exchange rate in Zambia.

4.0 Model Specification and Estimation Methods

In modeling the impact of drought on the exchange rate, I consider a reduced form VAR equation $(1a)$ with n endogenous variables taken as the model summarising the sampling information contained in the data used to address the objective of exploring the dynamic behaviour and underlying factors behind the Zambian Kwacha/US Dollar exchange rate during episodes of droughts.

$$y_t = \alpha + \sum_{i=1}^{L} \boldsymbol{B}_i y_{t-L} + \varepsilon_t \qquad (1a)$$

where y_t = vector of variables of interest

$t = 1, - - - - -, T$;

$\alpha = 1 \times \rho$ unknown vector;

$\boldsymbol{B}_i$ = unknown $\rho \times \rho$ matrix of coefficients, $i = 1, - - - - -, L$; and

$\varepsilon_t = \varepsilon_1, - - - - -, \varepsilon_T$, the independent and identically distributed error terms.

The error terms are normal i.e. $N_\rho(0, \Sigma)$ with $\rho \times \rho$ unknown covariance matrix $\boldsymbol{\Sigma}$. In the VAR above, L is the lag and the unknown matrix of the regression coefficients α' and β_i' is represented by $\boldsymbol{\Phi}$ in equation (1b), which is an ideal representation if the VAR has to be estimated with Bayesian techniques:

$$E\left[(\boldsymbol{\Phi}_k)_{i,j}\right] = \begin{cases} \delta \ \ if\ j = i, k = 1 \\ 0 \quad \text{otherwise} \end{cases}, \qquad V\left[(\boldsymbol{\Phi}_k)_{i,j}\right] = \begin{cases} \dfrac{\lambda_1 \lambda_2}{k} \dfrac{\sigma_i}{\sigma_2}\ , \ k = 1, \ldots\ldots, p \\ \lambda_0 \sigma_i, \end{cases} \qquad (1b)$$

where $(\boldsymbol{\Phi}_k)_{i,j}$ represents the elements in position (i, j) in matrix $\boldsymbol{\Phi}$ and $\boldsymbol{\delta}$ is the prior mean that takes the value 0 or 1. If the VAR is specified in levels, $\delta = 1$. But if the VAR specification is in growth rates, then $\delta = 0$. The hyper parameter λ_1 controls the overall tightness with regard to the way the prior influences the posterior distribution. If $\lambda_1 \to 0$ or indeed $\lambda_1 = 0$, the posterior equals the prior and the data do not influence the estimates and when $\lambda_1 \to \infty$, the posterior expectations are consistent with the ordinary least square (OLS) estimates.

Rainfall data is allowed to interact with the exchange rate in line with the theoretical framework by Feyen, Utz and Huertas (2020) but in a VAR system of equations. The impact of drought on the exchange rate is estimated with Bayesian techniques based on sign restrictions to help trace the dynamic impulse response functions. The Bayesian VAR is adopted because economic, social and nature-based variables interact as a system, and as stated by Cha and Bae (2011), sign restrictions are only possible in a Bayesian setup. In addition, Bayesian techniques are good for data with few (short) observations (Harjes and Ricci, 2010). The Bayesian VAR approach works in three steps that involve setting a prior belief about parameters of the model a researcher is interested in, collecting the data and setting the likelihood that is aimed at reflecting the data generating process of the observed data, and computing the posterior distribution after the data has been allowed to interact with the prior as per the likelihood function.

In Bayesian analysis, the prior is a probability distribution and could be expressed as $P(\theta) \sim N(\widetilde{\theta_0}, \Sigma_0)$ if it is a normal distribution, for example. The collected data (y) and its likelihood, $\mathcal{L}(y/\theta)$, interact with the prior belief based on the Bayes Theorem in a way presented in equation (1):

$$P(\theta/Y) = \frac{P(y/\theta)P(\theta)}{P(y)} \qquad (2a)$$

The denominator $P(y)$ is a data density that can be evaluated through integration as

$$P(y) = \int (y/\theta)P(\theta)d\theta \qquad (2b)$$

Thus, the posterior takes the form:

$$P(\theta/Y) = \frac{P(y/\theta)P(\theta)}{\int (y/\theta)P(\theta)d\theta} \qquad (2c)$$

The posterior distribution is what matters to a researcher with Bayesian interest as it provides more information about the parameters, θ, given the available data, y (Koop et al, 2007). The likelihood function, $P(y/\theta)$ (alternatively expressed as $\mathcal{L}(y/\theta)$), implies that a value of θ for which $P(y/\theta)$ is large is more likely to be "true" than the value of θ for which

$P(y/\theta)$ is small. Both inferences and decisions concerning an observation of the data y are based on the information in the likelihood function for the observed data y.

In the Bayesian approach, θ is considered a random variable and the probability quantifies variability and the uncertainty that arises from randomness unlike with the frequentist. The measure of uncertainty in the frequentist approach is through the p-value or level of significance. For instance, a level of significance of 5 percent ($\alpha = 5\%$) implies a 95% confidence interval ($CI = 95\%$) in repeated sampling, and does not imply in probability that the true value of θ has a 95% chance (probability) of being true (Van de Schoot and Depaoli, 2014). However, Bayesian probability quantifies uncertainty such that a 95% credibile interval is a statement that there is a 0.95 probability of finding θ in the 95% interval (Van de Schoot and Depaoli, 2014). Sims and Zha (1999) introduced error bands for Bayesian VAR generated impulse responses to shape uncertainties with tighter bands implying low uncertainties around the parameter of interest.

From equation (1a) stated earlier, ε_t might not have economic interpretation because some elements may be cross correlated among the equations in the VAR system (Enders, 2008). This notwithstanding, one may derive economic meaning from the structure primarily because in economic theory, a one step ahead forecast errors of a reduced form VAR is linked to structural innovations (Chadha *et al.,* 2010; Cha and Bae, 2011; Danne, 2015). This takes the form presented in equation (3):

$$\boldsymbol{A}\varepsilon_t = e_t \tag{3}$$

where $\boldsymbol{A}$ is $n \times n$ matrix of structural parameters with e_t being structural shocks that are identically and independently distributed with zero mean unit variance. Formally, $e_t \sim iid(0,1)$. The structural parameters can be recovered from the reduced form VAR when the system conforms to equation (4) and use ordinary least square (OLS) method to obtain parameter values:

$$\boldsymbol{A}\boldsymbol{\acute{A}} = \Sigma = E[\varepsilon_t \acute{\varepsilon}_t] \tag{4}$$

To specifically recover structural shocks from the estimated $\widehat{\varepsilon_t}$, there is need for the identification of $\boldsymbol{A}$ and requires at least $n(n-1)/2$ number of restrictions to uniquely identify the elements of $\boldsymbol{A}$ because it has n^2 unknown elements (Enders, 2008; Chadha *et al.,* 2010; Cha and Bae, 2011; and Danne, 2015).

This study uses the sign restriction approach based on the Uhlig (2005) *penalty – function* method for the identification and recovering of the structural shocks involving rainfall, exchange rate (exr), foreign exchange supply (fxs) and foreign exchange demand (fxd) variables as in equation (5). The robust test of the estimations is achieved with the Fry and Pagan (2011) *Median – Target (MT)* method.

$$\boldsymbol{y} = f(rainfall, exr, fxs, fxd) \tag{5}$$

The justification for the *penalty – function* is because the method is designed to deal with one shock unlike other methods. This is the primary objective of this research as it is related to establishing how a negative shock to rainfall (which is a significant decline from its long trend level, a drought condition) affects the exchange rate and other variables related to it. Economic variables interact in a system such that shocks from respective variables affect each other either in isolation or jointly (Uhlig, 2005). This technique can isolate the impact of one shock on other variables in the system.

The other justification is that while Baumeister and Hamilton (2015 and 2019) provide a sophisticated algorithm for estimating structural VARs with sign restrictions, my sincere belief is that the tool is ideal for identifying supply and demand shocks on a particular variable when demand and supply are not expressly modelled whilst providing prior information on some parameters, including those in the contemporaneous matrix. This is not the case with the current study because foreign exchange demand and supply variables forms part of the VAR. It may also be difficult to justify the need to identify the contemporaneous effect of drought on the exchange rate and other variables in the system since drought is an event so characterised with some passage of time.

The *penalty – function* procedure uses the Normal – Wishart prior in the estimation of $\boldsymbol{B}$ and Σ. For sign restriction and draws from the posterior distribution. The *penalty – function* method finds an impulse vector α based on the Givens matrix that gets as close as possible to satisfying an imposed sign restriction by minimising a penalty for sign restriction violations (Uhlig, 2005 and Danne, 2015).

The Bayesian process is achieved through Markov Chain Monte Carlo (MCMC) simulations with an uninformative prior, usually the uniform distribution, used as a prior distribution for making successful draws. Therefore, in this procedure, one computes the cumulative impulse responses and check whether the range of impulse response is compatible with the sign restrictions. However, one needs to bear in mind that there is a possibility of generating rejected draws. In this situation, the credibility of the process, which essentially defines how well the model is specified and fits the data, can be deduced from the number of rejected draws (Danne, 2015). This is one of the reported MCMC outputs. Zero or few rejections implies the estimation process is good. Therefore, too many rejections are indicative of the presence of better alternative models that fit the data and satisfies sign restrictions.

In summary, the procedure is presented below (see Uhlig, 2005; Chadha *et al*., 2010; Busch *et al*., 2010; Danne, 2015 for a detailed technical description):

a. Assuming the information in the data for the variables of interest being explained by an unrestricted VAR(p) as in equation (1), choose an optimal lag length for the unrestricted VAR. Then estimate it as a Bayesian VAR of the order suggested by the lag length criteria to obtain a posterior distribution $\widehat{\boldsymbol{B}}$ and $\hat{\Sigma}$ based on an appropriate prior for $\boldsymbol{B}$ and Σ. The Normal Inverted – Wishart family of priors is usually used in the estimation of $\boldsymbol{B}$ and Σ.

b. Draw from the posterior distribution the innovations using a Cholesky decomposition. The Cholesky decomposition is for ensuring that shocks are orthogonalised. It is just an identification strategy. Letting $\widetilde{\boldsymbol{A}}$ to be the Cholesky decomposition then:

$$\Sigma = \widetilde{\boldsymbol{A}}\widetilde{\boldsymbol{A}}' \tag{6}$$

c. For sign restrictions, set an orthogonal impulse vector $\boldsymbol{R}$[3] and randomly draw from it, with each successful draw being multiplied by the innovations from the Cholesky decompositions to obtain the acceptable draws $\boldsymbol{G}$ such that:

$$\boldsymbol{G} = \widetilde{\boldsymbol{A}}\boldsymbol{R} \tag{7}$$

The draw resulting from the multiplication of each element of $\widetilde{\boldsymbol{A}}$ and $\boldsymbol{R}$ is accepted if it satisfies the imposed sign restriction(s). This is a repetitive process until a set number of draws is achieved to obtain the impulse responses.

A VAR model with a lag of 5 that ensures all roots were within the unit circle[4] is used for monthly data in which variables, namely, rainfall, foreign exchange supply, foreign exchange demand and the exchange rate. They are admitted as deviations from their respective trend, estimated with the help of the Hodrick-Prescott (HP) filter. The resultant model is a stable VAR as its characteristic roots lie within the unit circle and it is the underlying model representing the sampling distribution of the data at hand. A Bayesian VAR with sign restrictions is thus estimated.

The sign restrictions are summarised in Table 1 below and essentially only imposes one negative sign on the rainfall variable in the second model. The first model has no restrictions on all the variables while foreign exchange demand and supply as well as the exchange rate are unrestricted in the second model. From the first model, we want to learn how rainfall under normal conditions tends to affect other variables in the system. The second model naturally aims at providing information on the dynamics of the exchange rate in the wake of a drought situation, which is the very essence of this study. In both cases, the data used spans from January 1998 to December 2019 largely influenced by the availability of a consistent rainfall data.

Table 1: Sign Restrictions for the Bayesian VAR

Description	Rainfall	Forex Supply	Forex Demand	Exchange Rate
Model 1: BVAR's sign restriction	NA	NA	NA	NA
Model 2: BVAR's sign restriction	"—" (i.e.<0)	NA	NA	NA

s[3] This can be a Givens rotation or alternatively it can be the QR-decomposition employed in the Rubio-Ramírez *et al.*(2010) *rejection method* for sign restriction estimation procedure. The Q matrix is an orthogonal matrix while the R matrix is an upper triangular matrix. Essentially, a QR decomposition decomposes a Givens matrix say Z in such a way that Z=QR.

[4] Although both the Schwarz and the Hannan-Quinn information criteria suggested two lags while the Akaike information criterion suggested eight lags.

"–" is a negative sign, implying a deviation from the trend for the variable of interest

Further, a historical decomposition is also estimated as per specification in equation (1a), primarily because of the easiness with its implementation in empirical work and yet very informative with the information it generates in accounting for the effects of various shocks on a particular variable. A VAR with a lag of 5 is also used in this case, which is a stable VAR as its characteristic roots lie within the unit circle. Since all the variables considered in this study are first difference stationary, they therefore enter the VAR system in first difference of their log transformation. The other reason of differencing the data is to remove the trend and thereby understand the underlying behaviour in the series under consideration. Additionally, VARs are suitable for the data that is stationary. The variables used are the same as those in presented in equation 4 but with an additional one being copper prices.

Furthermore, copper price is also considered as one variable that can capture global shocks, which in essence may have a bearing on sentiments. Commodity prices can reflect the external sector dynamics and thus global business cycles (Chipili, 2016). Zambia being a small open economy (given its liberalised capital account) with a free-floating exchange rate, global impulses can easily affect its exchange rate (Roger, Smith and Morrissey, 2017). This can be through copper price fluctuations resulting in the exchange rate undergoing changes through the process described in Section 5, but also through foreign exchange earnings filtering into the domestic market (supply).

The use of copper price alongside the foreign exchange supply variable may seem to be conflicting given that copper proceeds account for over 70 percent of foreign exchange earnings in Zambia and may thus cause problems of multicollinearity. However, a visual inspection of the two variables show that they do not have a common stochastic process (Figure 2). Thus, the two variables can be used in the same estimation framework without worrying about the possibility of multicollinearity.

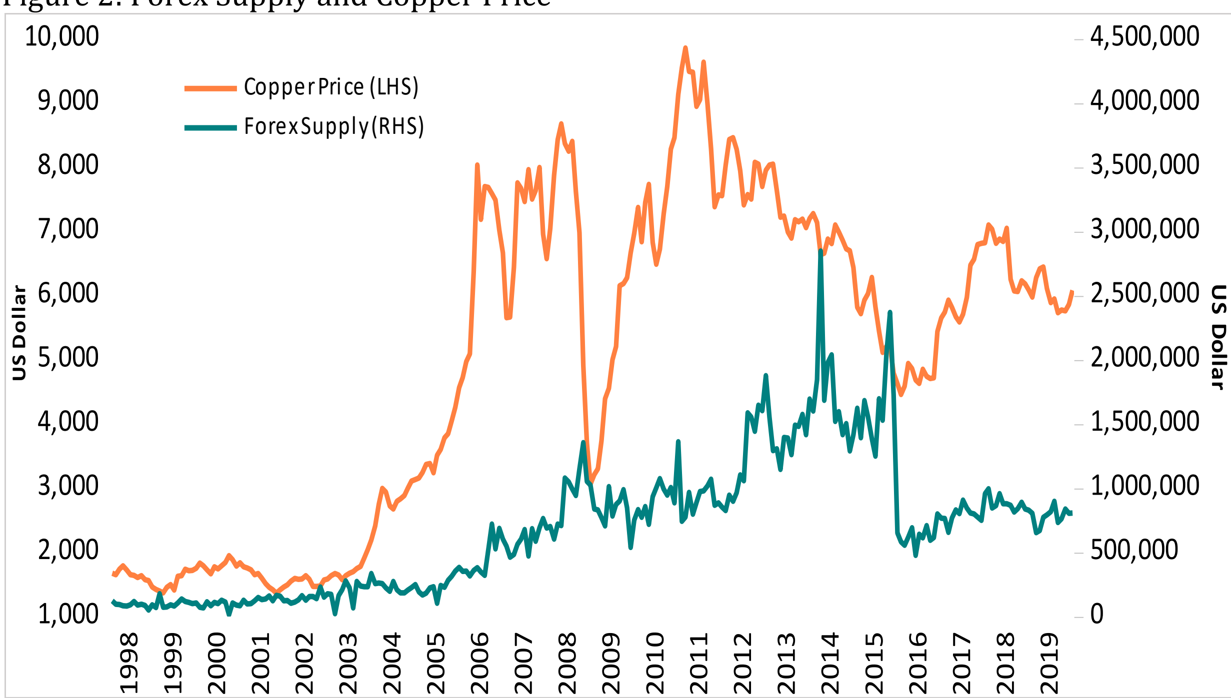
The historical decomposition of the shocks follows the Cholesky decomposition with the ordering starting with the most exogenous variable and ending with the most endogenous one in the baseline model. Hence, copper price comes first followed by foreign exchange demand and then foreign exchange supply. The exchange rate is ordered last. In the alternative specification, primarily aimed at testing the robustness of the results, the Cholesky decomposition ordering places the exchange rate in the first position followed by copper price with supply being ordered last. For the derivation of the historical decomposition, one can see papers by Fackler and McMillin (1998) Fackler and Parker (1994), and Burbidge and Harrison (1985), for example. To understand the drivers of exchange rate shocks in a drought period, one should look at historical decomposition of shocks in each drought period and see which shock, among copper prices, foreign exchange demand and foreign exchange supply shocks appear more pronounced. The one(s) that are relatively more pronounced in the drought periods are taken to be shocks accounting for the exchange rate depreciation in a drought episode.

5.0 Data Description and Sources

The study made use of five variables: the nominal exchange rate, foreign exchange demand, foreign exchange supply, rainfall in millimeters and copper prices in US dollars per metric ton. The exchange rate used is the price of the Kwacha per US dollar. Foreign exchange demand is the sale of foreign exchange by commercial banks to other banks (local through the interbank transactions and foreign financial institutions), bureau de change, Bank of Zambia (BoZ) and retail and corporate clients. Foreign exchange supply is the purchase of foreign exchange by commercial banks from other banks (local-interbank transactions and foreign), bureau de change, BoZ as well as retail and corporate customers.

Copper price is the selling price of the London Metal Exchange. In this study, the copper price is considered in the spirit of Roger, Smith and Morrissey (2017). In addition, changes in copper prices may signal the potential change to foreign exchange liquidity in the domestic foreign exchange market. A rise (fall) in copper prices may induce (un)favourable sentiments that may lead to the appreciation (depreciation) of the Kwacha against the US dollar. The effect on the exchange rate may take place through asset switching behaviour between domestic and foreign assets. A rise in copper prices for example may be a signal to economic agents that the country will soon experience an increase in foreign exchange supply that may lead to an appreciation of the Kwacha. To avoid a deterioration in their balance sheets (in local currency terms), economic agents reduce holdings of foreign assets and increase domestic assets. This reduces demand for foreign assets with a likely appreciating effect on the exchange rate. When the opposite happens, a depreciation of the exchange rate is likely.

Figure 2: Forex Supply and Copper Price

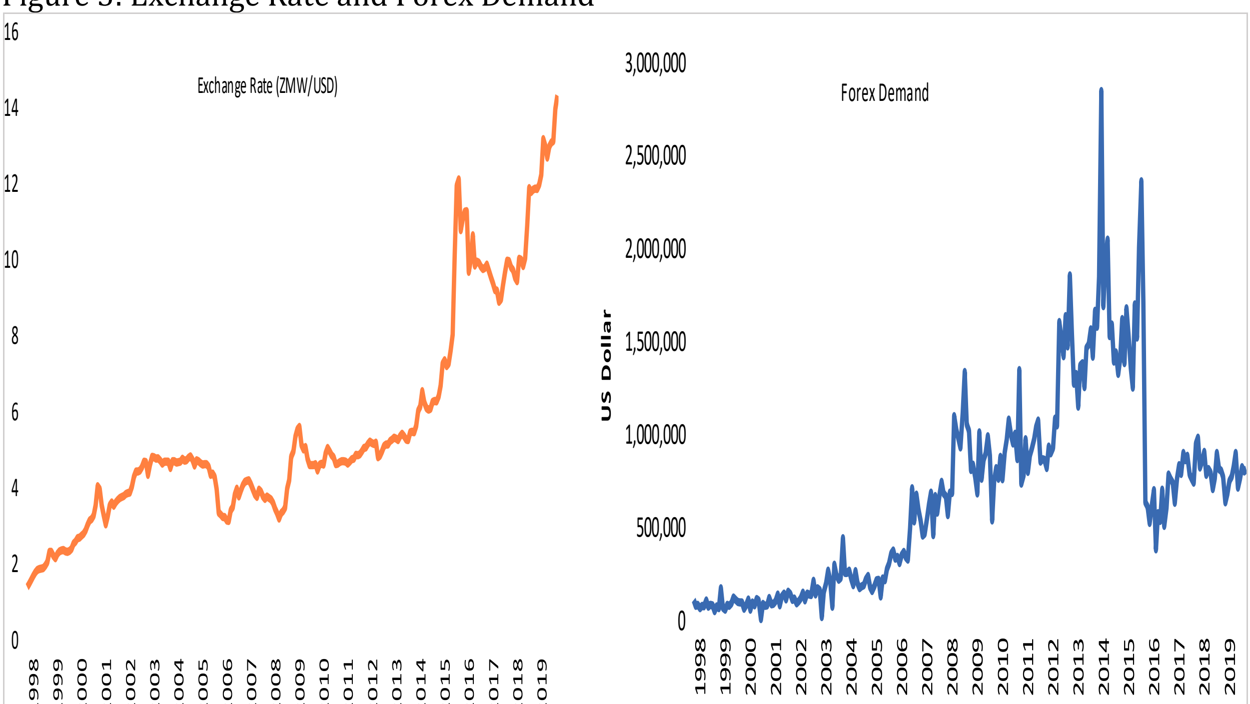


Nonetheless, the two series have trends, an indication that both series are likely to be first difference stationary. This is indeed confirmed by the Augmented Dickey-Fuller (ADF) unit root test results (Table 2). Both copper price and foreign exchange (Forex) supply are integrated of the order one (i.e. I(1) process), which is a first difference stationary process. A visual inspection of the exchange rate and foreign exchange demand variables show the two series to have trends just like the previous two variables discussed (Figure 3). This is prima facie evidence that the two series could also be first difference stationary type of processes. Indeed, this is confirmed by the ADF unit root tests results.

Table2: Augmented Dickey-Fuller Unit Root Test Results

Variable	Levels	P-Values	First Difference	P-Values	Order of Integration
Copper Price	-2.246857	0.4612	-11.45621	0.000000	I(1)
Forex Supply	-3.127841	0.1020	-20.88931	0.000000	I(1)
Forex Demand	-3.128975	0.1018	-14.91665	0.000000	I(1)
Exchange Rate	-0.464770	0.9846	-11.98992	0.000000	I(1)

Figure 3: Exchange Rate and Forex Demand

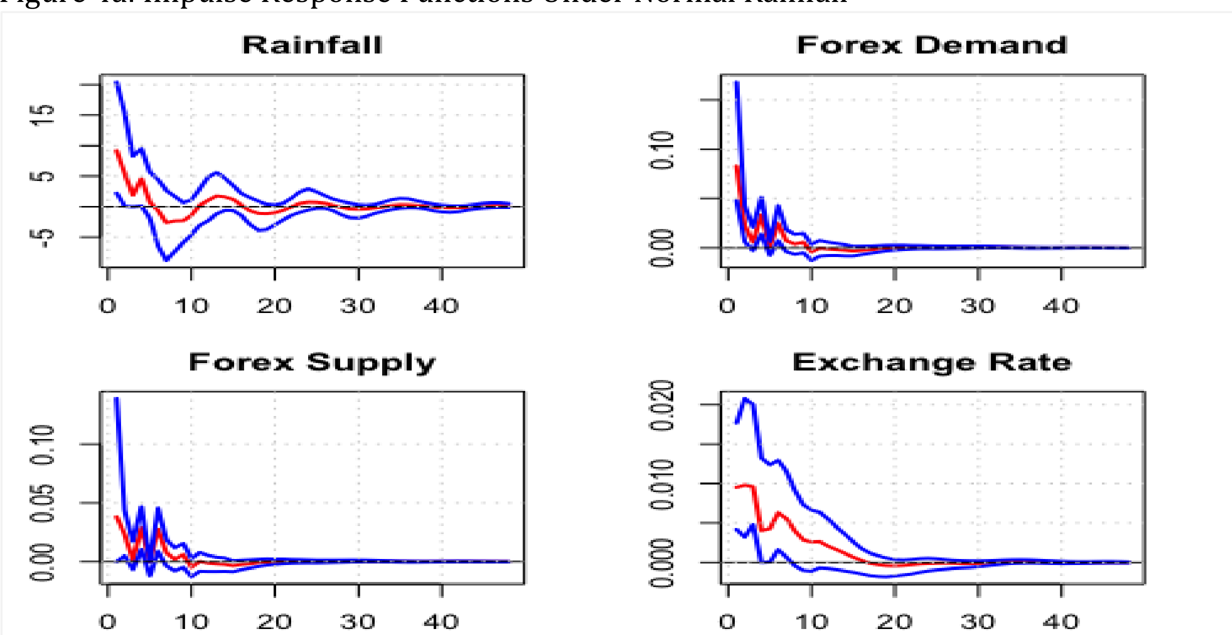


6.0 Empirical Results and Discussion

6.1 Bayesian Estimation Results

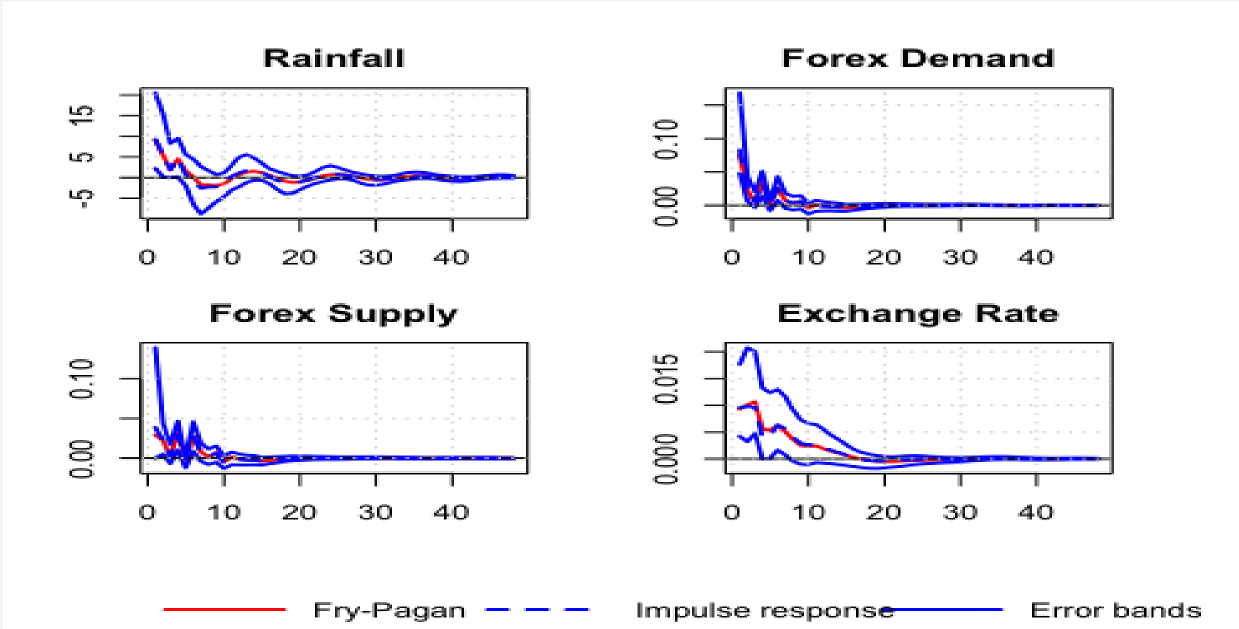
Based on Bayesian estimations with no sign restrictions (i.e. Model 1), the results (see Figure 4) show the exchange rate has an inherent tendency of deviating from its long-run trend in the first quarter despite rainfall being above its long-run trend. The rise in foreign exchange demand may be the reason as it is higher than supply. The depreciation behaviour of the exchange rate during the rainy season under normal condition (i.e. during a favourable rainy season) is offset after March (end of the rain fed agricultural production season, which is the time most crops are produced in Zambia). Further, the results show that foreign exchange demand and supply alike can be predictable given the tight credible intervals around their estimates. However, rainfall and exchange rate behaviour are characterised by some uncertainty given relatively high credible intervals before the impact of the shock dies out. In case of the rainfall, this can easily be explained because over the sample period, not less than five drought episodes were recorded.

Figure 4a: Impulse Response Functions Under Normal Rainfall



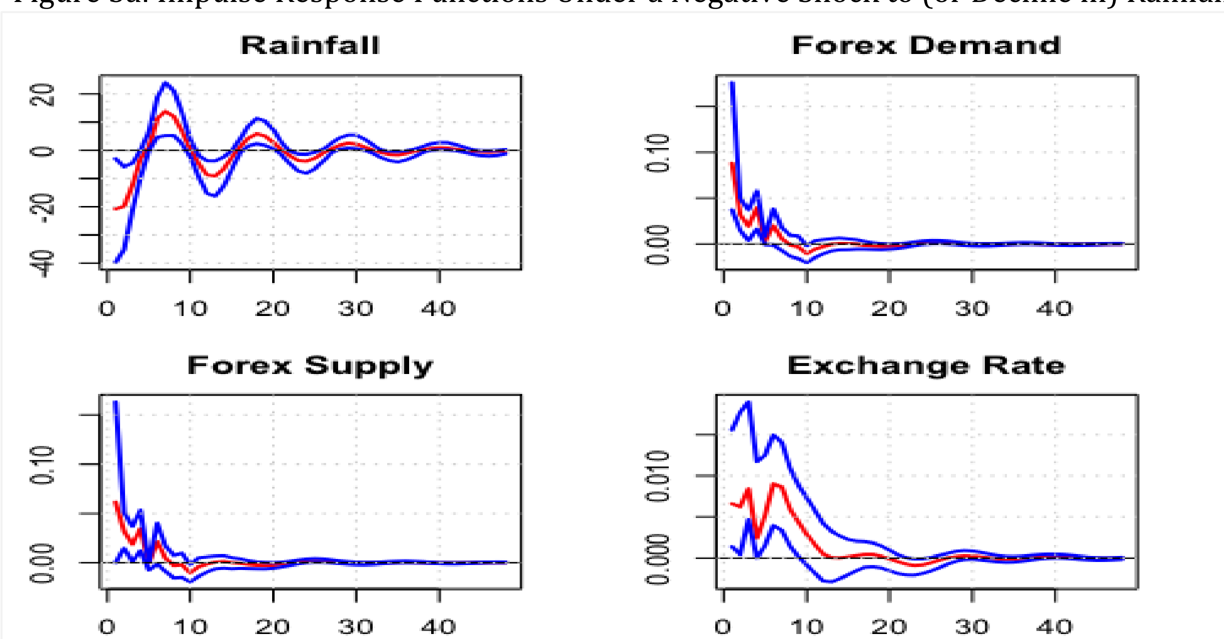
The estimates are robust to the *Fry and Pagan Median Target* estimation method given the impulse responses being in the infinitesimal (very close) neighbourhood (Figure 4b). Therefore, the model has fitted the data well and the information provided can be relied upon.

Figure 4b: Impulse Response Functions Under Fry and Pagan Robustness Test



When the rainfall variable is negatively shocked (i.e. Model 2) and thus rainfall is assumed to deviate from its long-run trend, an indication of a drought condition, the exchange rate depreciates as well but with some heightened volatility (Figure 5a) when compared to the condition of normal rainfall (Figure 4a).

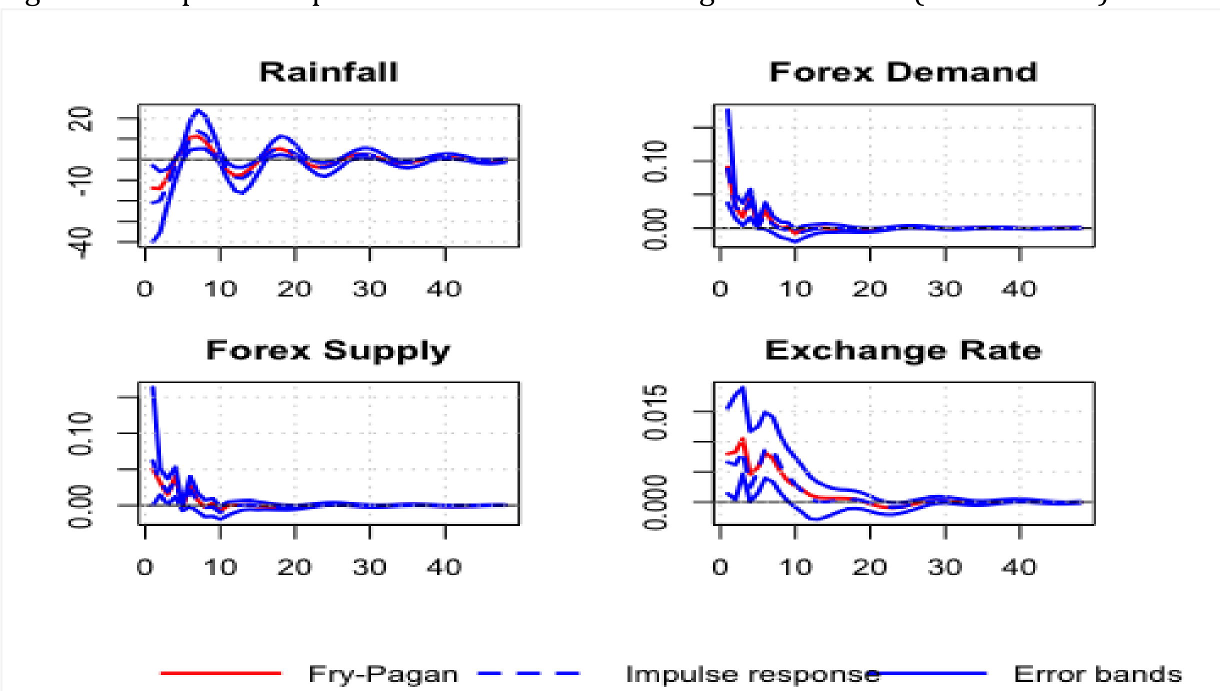
Figure 5a: Impulse Response Functions Under a Negative Shock to (or Decline in) Rainfall



Foreign exchange demand increases (is higher) relative to the normal rainfall condition and so is supply. The later may be due to central bank intervention aimed at smoothing exchange rate volatility. Consistent with this, the exchange rate moves to its long run trend smoothly although with a possibility of appreciating when viewed in light of the lower credible interval especially after the third quarter (from October). There is relatively high uncertainty around the exchange rate shock response estimation in a drought condition than under normal rainy condition as the credibility interval is comparatively wider. After a drought, the effect of the rainfall shock on itself, eases in the period April – September (second and third quarters) months of no rainfall, but its adverse effect reappears in October-December, the fourth quarter, and January – March, the first quarter of the following season (together making up the rain and agriculture season for Zambia).

The results above are consistent with the alternative estimation of the Fry and Pagan in view of the convergence obtained by the Uhlig and Fry and Pagan algorithms (Figure 5b). The estimations are robust in that regard and the results can therefore be relied upon.

Figure 5b: Impulse Response Functions Under A Negative Shock to (or Decline in) Rainfall

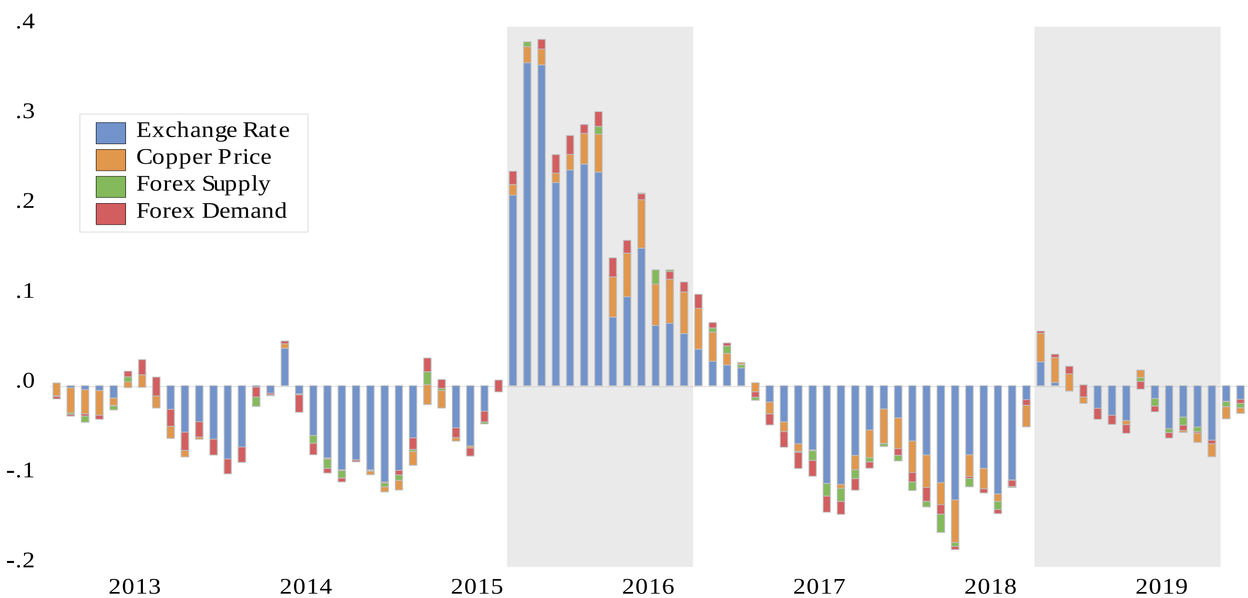


6.2 Historical Decomposition Estimation Results

The results in Figure 6 suggest that foreign exchange demand accounted for the most in the exchange rate variations experienced in episodes of drought in 2002/2003, 2004/2005, 2015/2016 (shaded periods). However, during the 2015/2016 drought, exchange rate depreciation was also affected by a shock to copper prices which declined following monetary policy normalisation in the US. Relatively lower copper price also explains the depreciation recorded in the early part of the 2018/2019 agriculture season that was characterised as a drought period. This implies that whenever the country experiences adverse weather conditions that causes drought and that there is a fall in copper prices, the exchange rate of the Kwacha against the US dollar may depreciate markedly. This was the case observed for example in 2015 and part of 2016 as well as the first part of 2018/2019 rain season. Supply shocks appear not to contribute to exchange rate variations during times of drought.

Figure 6a: Historical Decomposition of Exchange Rate Shocks, 2000-2007

Figure 6b: Historical Decomposition of Exchange Rate Shocks, 2013-2019



The results on copper price are generally in line with the findings by Roger, Smith and Morrissey (2017) who used a different specification. They established a strong influence of copper price shocks on the ZMW/USD exchange rate fluctuations in general. This phenomenon is broadly present in all moments of currency depreciation but also prevalent during the period of drought in Zambia. Generally, foreign exchange demand and adverse copper price shocks tend to have more influence on the exchange rate than foreign exchange supply shocks. Supply shocks could be muted maybe because of central bank purchases of foreign exchange from the markets for reserves build up (which is a good thing).

In view of the demand shocks playing a role in exchange rate depreciation during drought episodes as established by both the Bayesian technique and the historical decomposition, the natural thing to do is to ascertain what happens to the value of imports during drought periods. This is to determine if there is an increase in imports for items that would minimise the impact of drought on households and business with a possible link to exchange rate movements. In this regard, an interrogation of the trade data was undertaken. This revealed that during the last five drought episodes in the years 2013-2019, imports of relevant items that include food, petroleum products and electrical equipment and machinery that would mitigate the impact of drought on households or business virtually declined[5] (Table A1, Appendix). This could have been due to the depreciation of the Kwacha against the dollar that made imports expensive as more than usual amount of Kwacha was needed to obtain the same quantity of imports.

However, an assessment of the monetary accounts in the 'other' depository corporation survey obtained from BoZ generally shows an increase in commercial banks' net foreign assets (NFA) and foreign currency deposit liabilities (FCDL) in all the drought periods of the last five years except in 2019 when a decline in the NFA and FCDL was recorded (Table A2). This may suggest that in most of the drought periods where the foreign exchange demand shock was relatively pronounced, exchange rate depreciation could be driven by economic agents' behaviour of switching towards holding of more foreign assets than in non-drought periods. The rise in the holdings of foreign currency denominated assets leads to the increase in demand for foreign exchange and subsequently put pressure on the exchange rate.

Given the tendency for the FCDLs and consequently the NFAs for commercial banks to rise during drought periods, measures to constrain liquidity during drought periods may reduce demand for foreign exchange for placement into foreign currency deposits by economic agents.

The other likely optimal policy option should be a strategically crafted verbal intervention aimed at creating confidence in the market. Verbal interventions have been found to work well as they have helped central banks deliver exchange rate stability. Zhang, Li and Zhang (2017) show evidence that successive, rather than discrete, communications to the foreign exchange market reduce exchange rate volatility in China. This is somewhat in line with Hu et al. (2016) although their evidence shows actual intervention to be relatively more effective than verbal intervention. Whatever the case, there is some evidence of verbal intervention influencing exchange rate volatility and level to a desirable outcome, although actual intervention is relatively more formidable as established by Beine, Janssen and Lecourt (2009) for the US, euro area and Japan foreign exchange markets.

[5] This is with the exception of food items for 2019, although the increase is relatively small.

7.0 Conclusion

The problem of what is the likely dynamic behaviour of the exchange rate in the event of a drought has been addressed in this study. The Bayesian technique with sign restriction used to simulate a possible reaction of the exchange rate in a drought condition shows that exchange rate depreciation is accompanied by increased volatility than under normal conditions. The question of what drives the exchange rate depreciation in the wake of drought episodes in Zambia given the anecdotal evidence suggesting that the exchange rate indeed does depreciate during the time of drought events has also been explored. This is based on the historical decomposition technique in a standard VAR setup using the Cholesky ordering. The results suggest that shocks to foreign exchange demand largely account for the most of shocks causing exchange rate depreciation in drought episodes. Demand for foreign currency denominated assets tends to rise during drought periods as observed in the increase in commercial banks NFAs and FCDLs. Adverse shocks to copper prices, and, therefore, global events and sentiments, augmented the depreciation of the Kwacha especially during the 2016 and partly 2019 drought incidences.

In view of the increase in FCDLs and in turn the NFAs for commercial banks leading to the tendency for the exchange rate to rise during drought periods, interventions to drain liquidity during such periods may minimise economic agents' currency switch from local to foreign currency holdings. This may reduce pressure on the exchange rate to depreciate. Further, verbal interventions through strategic communication to the market is another option to minimise exchange rate volatility. Verbal interventions have been found to work well as they have helped central banks deliver exchange rate stability.

This study is not by any means exhaustive on the subject or problem at hand. In this regard, machine learning and neutral network algorithms can also be explored to establish factors driving exchange rate depreciation in times of drought.

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Appendix

Table A1: Annual Percentage Change in the Value of Imports

	2013	2014	2015	2016	2017	2018	2019
Food Items	-9.20	4.57	3.25	-6.46	10.41	0.72	4.08
Petroleum Products	15.75	31.32	8.07	-9.77	-15.78	14.74	-5.94
Fertiliser	25.86	-12.79	8.20	-19.20	85.27	-20.23	-22.06
Chemicals	11.83	-26.03	38.64	-9.34	55.50	-31.95	-14.49
Plastic and Rubber Products	12.99	-13.62	-14.27	-14.29	23.15	22.99	-6.71
Paper and Paper Products	4.47	-11.96	-2.84	-16.11	11.65	15.76	-2.42
Iron and Steel and Items Thereof	40.56	-7.45	-28.78	-39.45	30.86	35.34	-13.23
Industrial Boilers and Equipment	20.96	-18.85	-17.10	-18.64	13.21	22.96	-18.33
Electrical Machinery and Equipment	25.83	12.56	-23.24	26.85	-35.24	32.59	-25.27
Vehicles	1.94	-10.18	-32.16	-17.24	6.81	67.16	-27.40
Ores, Slag and Ash	93.70	-8.86	-50.60	-0.25	46.40	23.77	-87.44
Other Imports	-94.93	-	-	809.32	78.34	-12.47	-9.87
Total	33.76	-6.87	-18.10	-19.13	20.77	7.84	-23.65

Source: Author's computation with data obtained from BoZ

Table A2: Annual Percentage Change in Commercial Banks NFAs and FCDLs

	NFA (USD Millions)	%change	FCDL (USD Millions)	%change
2011	630.12	-	1,773.23	-
2012	235.14	-62.7	1,718.63	-3.1
2013	527.09	124.2	1,892.66	10.1
2014	407.59	-22.7	1,731.86	-8.5
2015	650.79	59.7	1,843.84	6.5
2016	676.95	4.0	1,732.26	-6.1
2017	925.40	36.7	1,778.83	2.7
2018	1221.71	32.0	1,793.81	0.8
2019	907.75	-25.7	1,774.17	-1.1

Source: Author's computation with data obtained from BoZ