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Full Length Research Paper

Modelling extreme volatility in the daily exchange rates of the Kenya shilling against the U.S. dollar[i]

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This study used extreme value theory to establish if the volatility witnessed in the exchange rate of the Kenya Shilling against the U.S. dollar in the period 1999 to 2013 could have been predicted and also determine if the long-term stability in the exchange rate was violated in the period. The peak over threshold model is applied to the tail of the volatility process of exchange rate returns of the Kenya Shilling against the U.S. dollar. The results showed that despite episodes of extreme volatility, the long-term stability of the exchange rate was maintained during the period. However, implementation of policies that will increase and sustain the level of foreign exchange inflows into the country is necessary to mitigate the vulnerability of the exchange rate to external and domestic shocks. Specifically, policies to promote the export sector and those to increase the level of foreign exchange reserves held by the Central Bank of Kenya should be encouraged. The comparably extreme volatility witnessed in the period 2008 to 2010 showed that political stability is a key component of foreign exchange market stability in Kenya.

Key words: Volatility, Extreme Value Theory, Peaks over Threshold model, GARCH model

INTRODUCTION

Extreme value theory (EVT) attracted considerable attention after volatility was witnessed in the financial markets during and after the global financial crisis in 2008/2009. Like other currencies in the East Africa region, the exchange rate of the Kenya Shilling against the U.S. dollar witnessed significant volatility in 2011 that was attributable to various factors including a wide current account deficit due to a high import bill, (Central Bank of Kenya, 2012). The oil import bill, which peaked at 25 percent of total imports in 2011, exerted pressure on the current account deficit leading to exchange rate depreciation. The current account deficit widened from 4.6 percent of GDP[ii] in 2009 to 7.9 percent in 2011 and remained high thereafter, averaging 9.2 percent in 2012 and 2013 (Kenya National Bureau of Statistics, 2014). The Eurozone crisis exacerbated pressure on the

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exchange rate with the U.S. dollar strengthening as the preferred reserve currency. Consequently, the maximum exchange rate of the Kenya Shilling against the U.S. dollar reached a historical level of 105.96 in 2011 (appendix 1). The annual standard deviation of 6.18 for the exchange rate in 2011 was also the highest since 1999.

Extreme volatility in exchange rates creates uncertainty about future returns and can affect long-term investment decisions of companies involved in international trade. Exchange rate volatility can stifle international trade through excessive import and export price variability. The uncertainty created by exchange rate volatility can prompt firms to add a risk premium to prices of internationally traded goods thereby reducing the demand for such goods and slowing down economic growth (Becketti et al*.* 1989). Exchange rate volatility can also alter international capital flows. It can promote short-term and speculative capital flows which can hinder the effectiveness of monetary policy. This can be costly as the Central Bank resorts to drawdown on its reserves to intervene in the foreign exchange market in order to stabilise the exchange rate. In this regard, the Central Bank of Kenya (CBK) sold a significant amount of foreign exchange in 2008 and 2009 to dampen extreme volatility in the exchange rate (Central Bank of Kenya, 2009). Extreme exchange rate volatility therefore raises concerns on the effectiveness of the Central Bank in performing its core mandate of maintaining price stability. Consequently, the long-term economic growth envisaged in Kenya's *Vision 2030* development plan is predicated on macroeconomic stability (Republic of Kenya, 2007).

Various studies have analyzed the extreme movements in the financial markets with respect to currency crises, stock market crashes and large credit defaults in recent times. The peaks over threshold (POT) model of EVT have been advocated in these studies (Embrechts *et al*. 1997). Given the episodes of extreme volatility such as that in 2011, this study applies the POT model to the volatility process of the daily exchange rate returns of the Kenya Shilling against the U.S. dollar using daily data from January 1999 to December 2013. The volatility process is generated from the Generalized Auto-regressive Conditional Heteroscedasticity (GARCH) model introduced by Bollerslav (1986). The GARCH model is robust in modelling the volatility in financial data characterised by volatility clustering and hetero-scedasticity. In order to describe the extreme volatility, the POT model is applied to the tail of the volatility process.

A comparative analysis of the extent of volatility in selected periods of the study period is undertaken to establish periods of extreme exchange rate volatility.The trend in the occurrence times and excesses of the extremes of the volatility process is then analysed. The return period of extreme exchange rate returns was computed to establish the approximate recurrence interval of specific extreme observations. The main contribution of this study to the existing literature is the use of both the GARCH and EVT in the analysis of exchange rate volatility in Kenya.

The rest of the paper is divided into four sections. Section 2 provides the methodology adopted in the study; Section 3 describes the data used in the analyses; Section 4 reports the empirical results and Section 5 concludes the paper and provides policy recommen-dations.

LITERATURE REVIEW

The ability of macroeconomic models to predict volatility has been examined in literature. Although macroeconomic models have forecasting abilities, the most important factor in these studies was the lagged endogenous variable (Frankel et al*.,* 2008). Recent studies on modelling volatility in financial data therefore focus mainly on time series models.

The Autoregressive Conditional Heteroscedasticity (ARCH) and GARCH models are important tools in describing the volatility in financial data (Engle, 1982; Bollerslav, 1986). The GARCH family models stand out in capturing heteroscedasticity and volatility clustering in financial data. Although comparatively long lags are required in ARCH models, the GARCH (1, 1) is adequate in describing most financial time series (Bollerslav et al.,. 1992). However, GARCH models have been criticised in that they do not provide a theoretical explanation of volatility or what information flows are in the volatility generating process (Tsay, 2005). The model also responds equally to asymmetric shocks, and cannot cope with significantly skewed time series which results in biased estimates. Other variations of the GARCH model such as Exponential GARCH, Threshold GARCH and Power GARCH have been proposed to address some of these weaknesses (Floros, 2008).

The EVT approach is well established in literature, and provides a strong foundation to build statistical models to characterise extreme events (Resnick et al., 1996; Embrechts et al., 1997; McNeil et al*.,* 2000; Smith, 2003). Andreev et al. 2012 argue that EVT and POT model are robust for estimating measures of tail risk under irregular volatility in market. The models are based on sound statistical theory and allow for extrapolation beyond the range of the data. McNeil et al*.* (2000) proposed a two stage approach where the GARCH model is fitted to return data, and EVT used to model the tail of the residuals from the estimated GARCH model. The approach, which is similar to the one used in this study, addresses the drawbacks of the previous EVT methods which failed to capture the stochastic volatility exhibited by most financial return data.

The implementation of EVT has various challenges including scarcity of extreme data, determining whether the series is heavy-tailed, choosing the threshold or beginning of the tail, and choosing the methods of estimating the parameters (Resnick et al., 1996). Various diagnostic tools including QQ-plots, sample mean excess plots, scaled excesses and inter-arrival times, and the Hill plot have been suggested to address these challenges (Embrechts et al*.,* 1997; Smith, 2003). The EVT approach may still be an accurate approximation of the actual distribution function of the extremes even if the independent and identically distributed (*i.i.d.*) assumptions on the data fails (McNeil, 1997).

METHODOLOGY

Generating the exchange rate return volatility process

The GARCH model is specified in line with Bollerslav (1986). Let (Z_n) be a sequence of *i.i.d.* random variables such that $Z_t \sim N(0,1)$. Then, ε_t is the $GARCH(p,q)$ process if $\varepsilon_t = \sigma_t Z_t$, $t \in \mathbf{Z}$ with $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2$, $t \in \mathbf{Z}$

Where $\sigma_t^{\ 2}$ is a non-negative process, and $\alpha_0 > 0$, $\alpha_i \geq 0$ for $i = 1, ..., p$ while $\beta_i \geq 0$ for $i = 1, ..., q$. The non-negativity restrictions on the parameters ensure positivity of the variance $\sigma_t^{\ 2}$. The sizes of the parameters α_1 and β_1 determine the short-run dynamics of the resulting volatility process in the GARCH (1, 1) model. A large ARCH error coefficient α_1 implies that volatility reacts significantly to market movements. Similarly, a large GARCH coefficient β_1 indicates that volatility is persistent. A high α_1 coefficient relative to β_1 indicate that volatility tends to be more extreme. Bollerslav (1986) reports that a necessary and sufficient condition for the weak stationarity of the GARCH model is $\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$. However, strict stationarity of the GARCH (1, 1) model requires that $E\left(\log(\alpha_1 Z_t^2 + \beta_1)\right) < 0$ which allows for $\alpha_1 + \beta_1$ being equal to or slightly above 1 (Nelson, 1990). Stationarity of the GARCH model ensures that the behaviour and properties of the estimators do not change over time and that the persistence of shocks is not infinite. The GARCH (1, 1) model is estimated by maximum likelihood estimation (MLE) specifying the density of the error term ε as a generalised error distribution (GED), (Nelson, 1990). The positive shape parameter ν for the GED measures the thickness of the tails. The GED yields the normal distribution for $\nu = 2$, and the Laplace or double Exponential distribution for $\nu = 1$. The density has heavier tails than the normal distribution for $\nu < 2$, and thinner tails for $\nu > 2$. The GARCH effects in the models are examined using correlograms of the squares of the exchange rate returns. Autocorrelations larger than the critical values give evidence of presence of GARCH effects.

Modelling extremes in the volatility process of exchange rate returns

In the POT model, excess sizes and exceedance times of a threshold *u* are modelled as a two dimensional homogeneous Poisson process (Embrechts et al., 1997). The model is formulated such that, first, the corresponding excesses over the threshold *u* are independent and distributed as a Generalised Pareto Distribution (GPD). Denoting the threshold by *u* and the shape parameter by ξ, the conditional distribution of excess values of X over u converges to the GPD as the threshold gets large. The GPD model is specified as follows:

$$G_{\xi,\beta}(x) = \begin{cases} 1 - \left(1 + \xi \dfrac{x}{\beta}\right)^{-\frac{1}{\xi}} & \text{if } \xi \neq 0 \\ 1 - e^{-\frac{x}{\beta}} & \text{if } \xi = 0 \end{cases}$$

Where $x \geq 0$ and $\beta > 0$ is the scale parameter, and the estimate of the shape parameter ξ determines the weight of the tail. Distributions for which $\xi > 0$, Frechet case, are called heavy-tailed and can be used to model large observations while distributions for which $\xi = 0$ are called thin tailed and correspond to all the common continuous distributions of statistics. The QQ-plot and sample mean excess plots can be used to determine the appropriate threshold for the GPD models. The QQ-plot also checks the validity of the distributional assumptions. Plots of the shape estimate for the GPD over a variety of thresholds are also used to reinforce the judgement in choosing the appropriate thresholds using the QQ-plot and sample mean excess plot (Embrechts et al*.,* 1997). In addition, the Hill plot can also be used to find the optimal threshold for the GPD model. The W-statistic $W_i = 1/\xi \log\left(1 + \xi(X_i - u)/(\beta + \xi u)\right)$ which refers to scaled excesses is analysed to avoid the subjectivity in the threshold selection using the mean excess over threshold plot (Smith, 2003). If all the assumptions on the GPD model are correct including the selected threshold u and the time span, the W_i 's are independent and exponentially distributed variables with mean 1. The GPD has finite mean for the shape parameter of $0 < \xi < 1$ and finite variance of $0 < \xi < 0.5$. Maximum likelihood regularity conditions are achieved and the maximum likelihood estimates are asymptotically normally distributed. The approximate standard errors for the estimators of β and ξ can therefore be obtained using *i.i.d.* from the Fisher Information Matrix.

Second, excesses of *i.i.d*. observations over a threshold *u* occur at times of Poisson process. If the exceedances of the threshold occur at times of a homogeneous Poisson process with constant intensity which is expressed as $\lambda_u = \left(1 + \xi u / \beta\right)^{-1/\xi}$, then the scaled inter-arrival times of exceedances given by $Z_k = \lambda \times (T_k - T_{k-1})$, should be *i.i.d*. exponential random variables with mean 1. Where T_k is the time of the k^{th} exceedance and $T_0 = 0$. Finally, excesses and exceedance times are independent of each other. The distribution of the *W* and *Z* values is

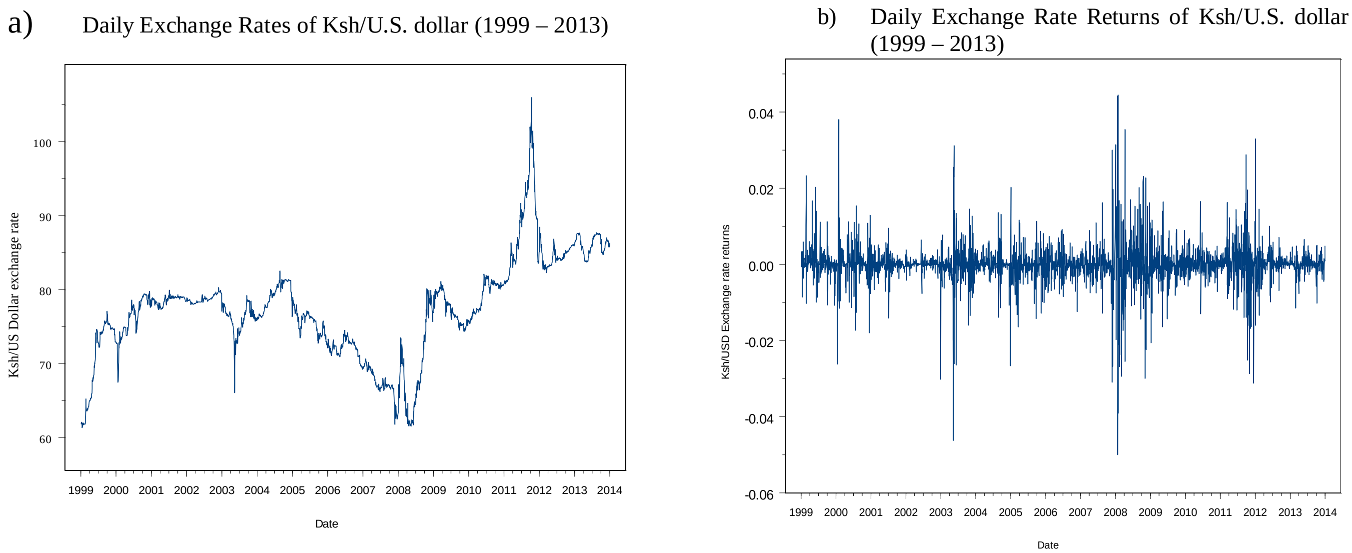

Figure 1. Trends in the daily exchange rate of the Kenya Shilling to the U.S. dollar (left panel), and exchange rate returns (right panel). *Source: CBK*

only approximately exponential since we do not know the true values of the GPD parameters and these have to be estimated. The diagnostic checks for the fitted POT model are based on Smith (2003). Scatter plots of W_i and Z_k values against the order of occurrence are used to check for identical distribution of these values. Any variation of these values with time would suggest a trend in the model. Smaller Z_k values indicate that exchange rate returns are becoming smaller. Plots of ordered W_i and Z_k values against expected exponential quantiles are used to check the exponential assumption on the distribution of these statistics. Approximate linearity of these plots would suggest that the exponential fit is good. The use of sample correlograms to check for independence of the W - values has a weakness in that the GPD has infinite variance for $\xi \geq 0.5$. Theoretical autocorrelations do not exist for this range of ξ.

Estimation of the parameters of the GPD is by numerical MLE method (Embrechts et al. 1997). The estimates for the parameters ξ and β are obtained by solving the simultaneous equations based on the log-likelihood function as below:

$$\frac{\partial L\left(\hat{\xi},\hat{\beta}\right)}{\partial \hat{\xi}} = \frac{1}{\hat{\xi}} \sum_{i=1}^{n} \log\left(1+\hat{\xi}\frac{x_i}{\hat{\beta}}\right) - \left(\frac{1}{\hat{\xi}}+1\right) \sum_{i=1}^{n} \left(\frac{x_i}{\hat{\beta}+\hat{\xi}x_i}\right) = 0$$

$$\frac{\partial L\left(\hat{\xi},\hat{\beta}\right)}{\partial \hat{\beta}} = -\frac{n}{\hat{\beta}} + \left(\frac{1}{\hat{\xi}}+1\right) \sum_{i=1}^{n} \frac{\hat{\xi}x_i}{\hat{\beta}^2+\hat{\beta}\hat{\xi}x_i} = 0$$

The return period of specific extreme volatility is determined by computing a quantile x_p at the tail for a given probability p. An estimate of the tail quantile $\hat{x}_p, 0 \leq p \leq 1$ gives the return level associated with the return period $1/p$ (Embrechts et al. 1997).

Data

The exchange rates data used in the study consist of daily data of the Kenya Shilling exchange rates against the U.S. dollar (Ksh/U.S. dollar). The exchange rate was derived by the CBK as an average of buying and selling rates of commercial banks spot exchange rates. The data comprises of 3,251 observations for the period from 4th January, 1999 to 31st December, 2013. The choice of the U.S. dollar was informed by its relative proportion in the CBK's foreign exchange investment portfolio which comprised over 60 percent in U.S. dollar in December 2013 while the currency composition of imports was about 50 percent in U.S. dollars. The U.S. dollar is also the main reserve currency in the global currency markets. The data was obtained from the CBK website. The exchange rates are transformed and analysed as daily logarithmic changes or exchange rate returns, i.e. $X_t = \log(e_t / e_{t-1})$. The transformation makes prices independent of their unit and therefore comparable with each other (Mikosch, 2001). The plots of the exchange rate returns in Figure 1 reveals a characteristic dependence structure where large and small values tend to occur in clusters. This reflects volatility clustering in the data. The structure was consistent with empirical evidence as in Taylor (1986) in which financial data is heavy tailed, has changing volatility, and exhibits serial dependence.

Extreme volatility in the exchange rate data in the study period was attributed to various episodes. In order to rein in inflation and exchange rate volatility in 2011, the CBK adopted monetary policy responses through increases in the policy rate from 6.25 percent at the beginning of September 2011 to 18 percent in December 2011. The cash reserve ratio (CRR) for banks was also raised from 4.5 percent in May 2011 to 5.25 percent in December 2012. These measures, coupled with other regulatory announcements by the CBK in 2011 resulted in a rapid increase in interest rates. However, exchange rate stability was restored by the end of 2011 (appendix 1). Exchange rate stability in 2012 and 2013 was supported by increased foreign exchange inflows from diaspora remittances and foreign investment in equity through the stock market (Central Bank of Kenya, 2013). Previous episodes of extreme volatility in the exchange rate were witnessed in 2003 and 2008, Figure 1b. A significant amount of liquidity was injected in the banking system following the reduction of the CRR from 10 percent to 6 percent in

Table1 . Summary statistics for exchange rate returns for various sample periods.

	1999-2013	1999-2007	2008-2010	2011	2012-2013
Mean	0.0000882	0.0000061	0.0003360	0.000206	0.0000289
Median	0.0000000	0.0000000	0.0000486	0.000771	0.0000993
Maximum	0.0445000	0.0380640	0.0444660	0.028788	0.032967
Minimum	-0.0500000	-0.0462420	-0.050001	-0.031210	-0.016004
Standard Deviation	0.0049070	0.0042200	0.006714	0.006881	0.002966
Skewness	-0.1818530	-0.448220	0.029662	-0.714779	2.105694
Kurtosis	22.482270	24.276050	17.05133	7.290145	36.90063
Jarque-Bera Statistic	59,390.01	42,418.70	6,211.24	215.27	24,360.38
Jarque-Bera Probability	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Observations	3754	2245	755	253	501

June 2003. Interest rates declined drastically resulting in short-term capital outflows and consequent weakening of the exchange rate.

However, there were mixed trends as the exchange rate strengthened during the Safaricom Initial Public Offer in mid 2008 and privatisation of Telkom Kenya in 2007 that led to substantial foreign exchange inflows. However, the exchange rate weakened in August 2008 when the IPO started trading at the stock market following capital outflows (Central Bank of Kenya, 2008). The post poll jitters in the market in early 2008 and turbulence in the global economy following the global financial crisis contributed to the weakening of the Kenya Shilling against the U.S. dollar through October 2008 (Figure 1).

EMPIRICAL RESULTS AND DISCUSSION

The data analyses are conducted for the full data sample (1999 to 2013), and also across selected samples (1999 to 2007, 2008 to 2010, 2011, and 2012 to 2013). This facilitated comparison of the extent of extreme volatility across the periods and the impact of various domestic and global events in the selected periods on exchange rate volatility. The most notable events that had an impact on the exchange rate have already been highlighted in the sections 1 and 3. Descriptive statistics for the exchange rate returns X_t across various sample periods are presented in Table 1. The mean for exchange rate returns was higher in the period 2008 to 2010 compared to the other periods. The kurtosis coefficients are positive and higher than 3 across all samples while skewness coefficients are less than zero except for the periods 2008 to 2010 and 2012 to 2013. This indicates that the distributions of the exchange rate returns are not normal. The negative skewness coefficient for the entire sample indicates that the distribution of the returns is left skewed. This implies that appreciations in the exchange rate occurred more often in the study period. However, depreciations occurred more frequently in the periods 2008 to 2010 and 2012 to 2013 as depicted by the negative skewness coefficients.

Kurtosis coefficients are much higher than the 3 for a normal distribution indicating that the underlying distributions of the returns are leptokurtic. The Jarque-Bera tests for normality indicated that the distribution of exchange rate returns has tails which are heavier than that of the normal distribution. The autocorrelation and partial autocorrelation coefficients of the squared exchange rate returns show presence of serial correlation which was an indication of GARCH type of heteroscedasticity (appendix 2).

Estimated volatility models

The parameter estimates and the value of the Akaike Information Criterion (AIC) for the fitted GARCH (1, 1) models for the exchange rate returns are shown in Table 2. The AIC was computed for comparison between the GARCH models for the different samples. All models produced almost similar AIC values across the different sample periods. The estimated GARCH (1, 1) models are significant at 5 percent significance level with a high persistence of shocks in the volatility. The estimated α_1 and β_1 parameters are positive while their sum was slightly above 1 across all the estimated models. A higher estimated GARCH coefficient β_1 shows that volatility was more persistent in 2011 relative to the other periods. However, the estimated ARCH coefficient α_1 is higher in the period 1999 to 2007, an indication that volatility in the exchange rate returns tended to be more extreme compared with that in the period 2008 to 2010, 2011 and 2012 to 2013. The quasi maximum likelihood estimates, corresponding to the estimated GED parameters of the exchange rate returns are highly significant and correspond to distributions with heavier tails than the normal distribution.

The volatility process of the exchange rate returns based on the full sample (1999 to 2013) model is plotted in Figure 2 (left panel). The volatility was comparably more extreme in the period 2008 to 2010 compared with that in 2011. This was mainly attributed to the uncertainty

Table 1. Estimated GARCH (1, 1) models for exchange rates returns.

Sample	No. of observations	α_0	α_1	β_1	*GED Parameter*	AIC
1999 – 2013	3754	0.000000166 (5.64189)	0.461117 (10.39986)	0.715223 (42.93854)	0.68939 (42.93854)	-9.0244
1999 – 2007	2245	0.000000116 (3.92816)	0.568871 (7.45706)	0.714094 (32.65388)	0.57697 (34.35977)	-9.3079
2008 – 2010	755	0.000000739 (3.16788)	0.266644 (4.08030)	0.746316 (19.40346)	0.746316 (16.74591)	-8.2190
2011	253	0.000000373 (1.31281)	0.29286 (3.25924)	0.772078 (13.47551)	1.147325 (7.874760)	-7.6103
2012 – 2013	501	0.000000253 (2.49826)	0.48100 (3.74136)	0.61493 (9.18273)	0.80833 (14.0850)	-9.8090

Note: t-statistics are in parentheses.

a) Volatility process of exchange rate returns from GARCH (1, 1) model

b) Standardised residuals of exchange rate returns from the GARCH (1, 1) model

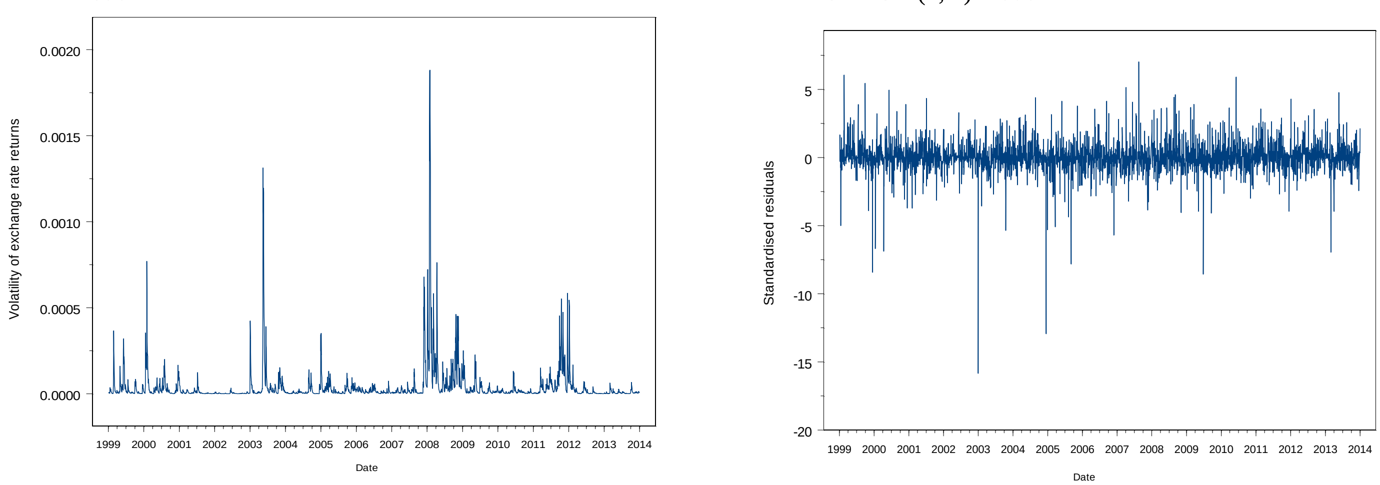

Figure 2. Volatility (conditional variance) process (left panel) and standardised residuals (right panel) of exchange rate returns derived from the GARCH (1, 1) model

in the foreign exchange market caused by the post poll crisis in Kenya, the impact of the global financial crisis and high oil prices which increased the import bill, Central Bank of Kenya (2008). The plot of the standardised residuals from the GARCH model of exchange rate returns (Figure 2 right panel) and the correlogram of squared standardised residuals in appendix 3 show that the model was well specified.

Extreme value models for the volatility of exchange rate returns

Data exploration

We first use the QQ-plot and sample mean excess plot to determine if the distribution of the volatility process derived from the full sample GARCH (1, 1) model of the exchange rate returns is heavy tailed, and then determine appropriate thresholds above which the volatility can be modelled by a GPD. The QQ-plot in Figure 3 (left panel) shows a concave relationship between the quantiles of the empirical and the exponential distribution which indicates that the distribution of the volatility is fat tailed. This plot, interpreted together with the shape plot in Figure 4 (right panel), shows that the sample points start deviating from linear behaviour and forms a concave shape at around 0.0000773. Similarly, the sample mean excess plot (Figure 3 right panel) for the volatility process is approximately linear and positively sloped from the above threshold which indicates heavy tailed behaviour.

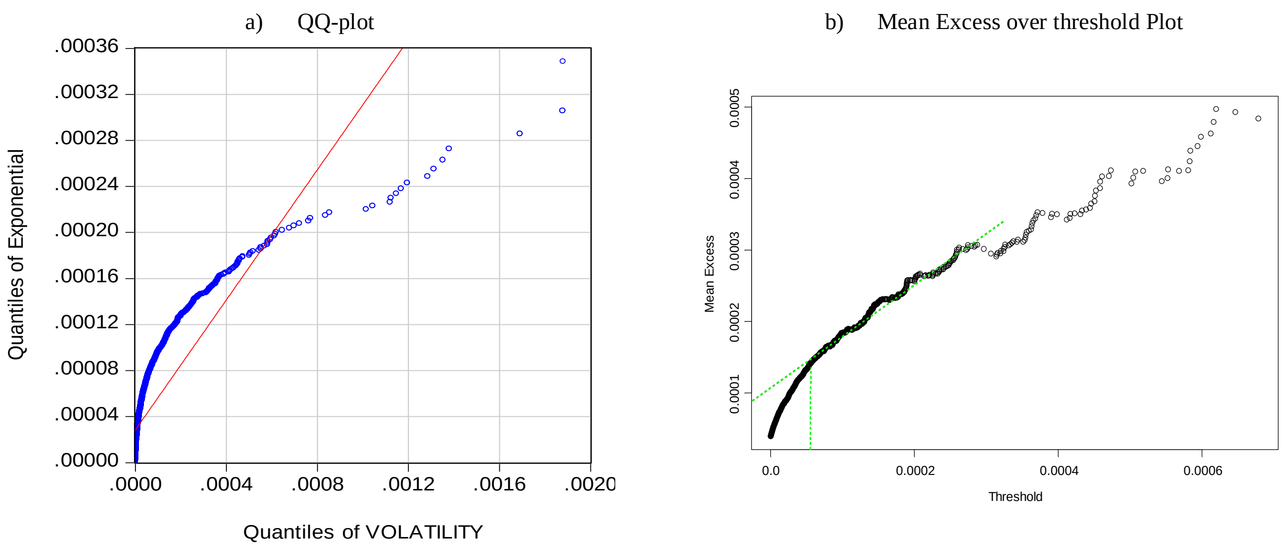

Figure 3. QQ-plot (left panel) and mean excess over threshold plot (right panel) for the volatility of exchange rate returns.

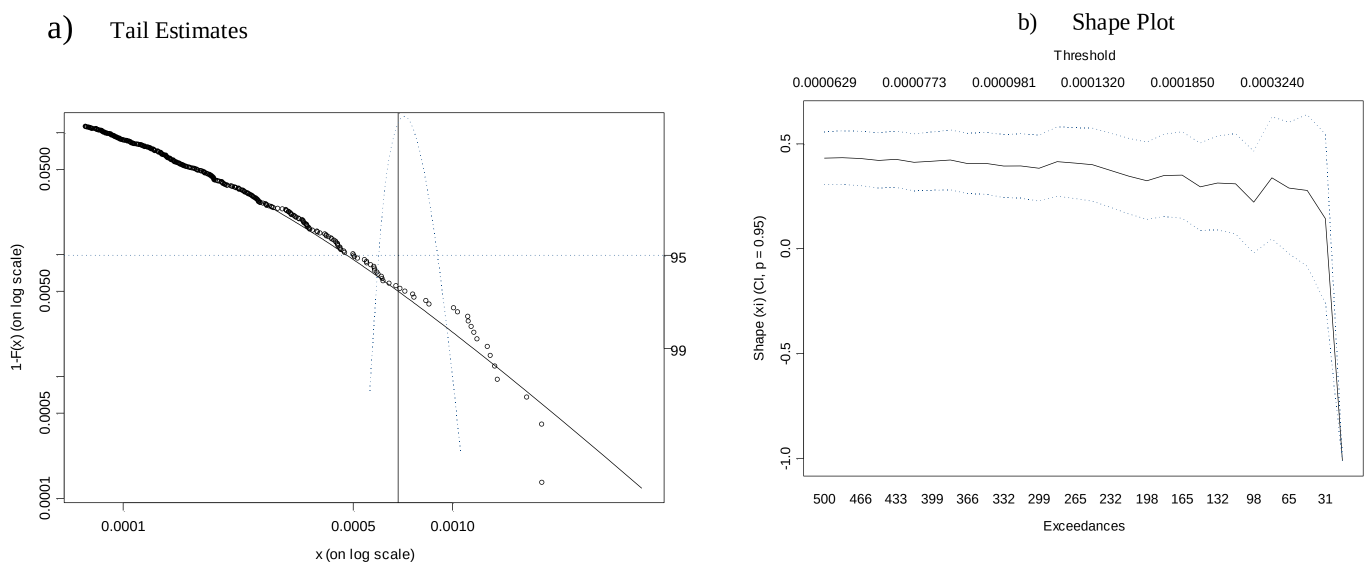

Figure 4. Tail estimates (left panel) and shape plot (right panel) of the volatility of exchange rate returns over various thresholds.

The shape plot provides estimates of the shape parameter over various thresholds. The distributions of excesses of the volatility process of exchange rate returns above this threshold can therefore be modelled by the GPD.

Estimated GPD models

As shown in Table 3, the fit of the GPD model to excesses of the volatility of exchange rate returns exceeding the selected threshold of 0.0000773 was highly significant for the full sample. The estimates for ξ and β were statistically significant at 5 percent signi-ficance level. The shape estimates indicate heavy tailed distributions with finite mean and variance. The GPD models are estimated using the EVIS SPLUS Software provided by Prof. Alexander McNeil.

The GPD model was also fitted to the excesses of the volatility exceeding the selected threshold across various samples. The threshold for the entire samples was assumed for the shorter samples to facilitate comparability of the estimated models. A higher value of the estimated shape parameter in the GPD model for the volatility of exchange rate returns in the period 1999 to

Table 3. Estimated GPD models for volatility of exchange rate returns.

Sample	*Threshold (u)*	*No. of exceedances of the threshold u*	$\hat{\xi}$	$\hat{\beta}$
1999 – 2013	0.0000773	417	0.4136621 (6.046733)	0.0000964 (11.851358)
1999 – 2007	0.0000773	162	0.4509568 (3.889077)	0.0000873 (6.895858)
2008 – 2010	0.0000773	162	0.4308485 (3.999177)	0.0001155 (7.571914)
2011	0.0000773	81	0.1976621 (1.104454)	0.0000859 (5.350629)
2012 – 2013	0.0000773	12	0.1789681 (0.351431)	0.0001219 (1.714973)

Note: t-statistics for the respective coefficient estimates are in parenthesis.

Table 4. Estimated quantiles and return period for extreme volatility of exchange rate returns.

Probability *p*	**Estimated Quantile** $\hat{x}_p$	**Expected return period in Days**
0.990	0.0004752	100
0.999	0.0014797	1000

2007 and 2008 to 2010 compared with that in 2011 and 2012 to 2013 indicates that volatility was more extreme in the earlier periods.

The GPD model for the full sample fitted most of the data well in the tails of the distribution as shown in Figure 4 (left panel). However, the GPD fit does not capture extreme observations in the period 29th January, 2008 to 4th February, 2008 corresponding to the peak of the post poll crisis which caused extreme volatility in the foreign exchange market due to political uncertainty. Volatility in the exchange rate returns was more extreme on 30th January, 2008.

The estimates of the shape parameters over various threshold levels with their 95 percent confidence levels are shown in Figure 4 (right panel). The plot shows that the shape estimates are all greater than zero, an indicator of heavy tails, have finite variance and quite stable at about 0.4 for thresholds in the range [0.0000629, 0.0000981]. The variability at the end of the plot is attributed to ahigh threshold resulting in fewer observations being used to estimate the GPD model.

Return periods for specific extreme volatility in exchange rate returns

Estimates of the 99 percent and 99.9 percent tail quantiles for the estimated GPD model are shown in Table 4. The occurrence of these levels of volatility in exchange rate returns is expected every 100 days (99 percent quantile) and 1000 days (99.9 percent quantile), respectively. Although the probability of occurrence of these levels of exchange returns is small (0.01 and 0.001, respectively), their impact on the economy can be detrimental. Exchange rate returns for the Ksh/U.S. dollar on 28th January, 2008, 30th January, 2008 and 1st February, 2008 were way above the estimated 99.9 percent quantiles for the GPD models. The extreme volatility of the exchange rate returns observed during these dates may not have been in the nature of the economy when they occurred.

Diagnostic tests on exceedances of the threshold

In this section, we analyse the trends in the excesses and exceedance times in the volatility of exchange rate returns over the selected threshold. Graphical analyses were conducted to check whether the excess amounts of the volatility of exchange rate returns are i.i.d. from the GPD, and whether the threshold exceedance times occur as a homogeneous Poisson process with constant intensity. The scatter plots of the scaled inter-arrival times Z against the order of their occurrence (right hand

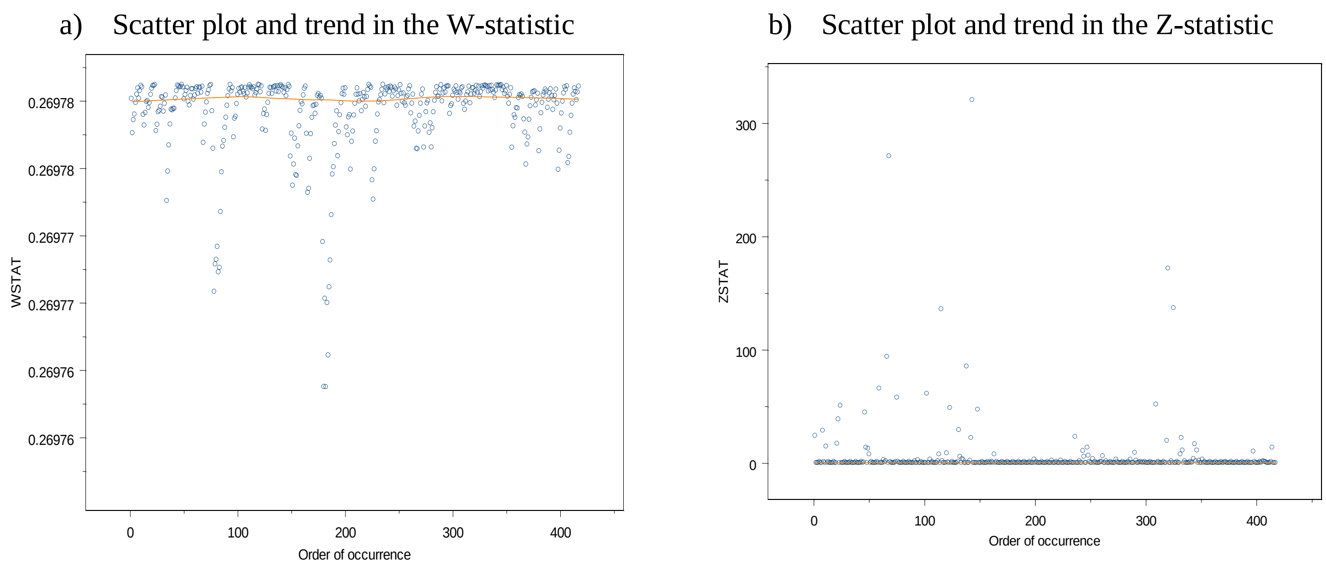

Figure 5. Diagnostic plots for the POT model of the volatility of exchange rate returns.

panel), and with superimposed Locally weighted scatter plot smoothing (Lowess) curves to capture the trend, indicate no significant trend (Figure 5). The Lowess is a smoothed mean value of the data and estimates the reciprocal of the intensity of the Poisson process (Embrechts et al*.*, 1997).

The correlograms of the Z-statistics and further tests revealed that the inter-arrival times of the threshold exceedances are independent. The QQ-plots of the scaled inter-arrival times reveal that these are approximately exponentially distributed which indicates that the threshold exceedances occur as a homogeneous Poisson process. Scatter plots of the W-statistics against the occurrence time with superimposed smooth curves to capture the trend show no significant trend (left hand panel).

The correlograms of the W-statistics did not show any evidence of non-independence. We deduce that the excess sizes for the volatility of exchange rate returns of the U.S. dollar are *i.i.d*. from the GPD. The QQ-plots of the W-statistics show that they are approximately exponentially distributed which indicates that excesses are *i.i.d*. as GPD.

Conclusion

This study used EVT to establish if the extreme volatility witnessed in the daily exchange rate of the Kenya Shilling against the U.S. dollar in the period January 1999 to December 2013 could have been predicted, and also determined if the long-term stability in the exchange rate was affected during the period. The GARCH (1, 1) model was applied in estimating volatility of exchange rate returns of the Kenya Shilling against the U.S. dollar and found to describe the volatility process well. The analysis revealed three key results for volatility of the exchange rate returns of the Kenya Shilling against the U.S. dollar in the study period. First, the quasi maximum likelihood estimates, corresponding to the estimated GED parameters of the exchange rate returns are highly significant and correspond to distributions with heavier tails than the normal distribution. Specifically, the volatility of exchange rate returns which exceed the threshold 0.0000773 can be modelled by the GPD. This threshold is therefore the indicative level for exchange rate returns above which the underlying depreciations in the exchange rate would be considered extreme which would require the CBK to intervene to stabilise the exchange rate. The estimated GARCH (1, 1) models show that the volatility in the daily exchange rates was comparatively extreme in the period 2008 to 2010.

The estimated return period for specific extreme volatility in the exchange rate returns showed that once after about 3 years (1000 days), we expect to observe an extreme volatility of 0.00148 in the exchange rate returns. This finding seems to mimic reality as depicted in Figure 1b which shows recurrence of extreme volatility in the exchange rate returns almost every three years. This extreme volatility requires the Central Bank to have adequate foreign exchange reserves to intervene to stabilise the exchange rate. However, the results showed a stable trend in the occurrence times of the extreme volatility and excesses above the selected threshold indicating that the long-term stability of the exchange rate was maintained in the study period.

This study shows that implementation of policies that will increase and sustain the level of foreign exchange inflows into the country is necessary to mitigate the vulnerability of the exchange rate to external and domestic shocks. These include policies to promote the export sector as well those to enhance the level of foreign exchange reserves held by the CBK. These measures will reduce the current account deficit and enhance the Central Bank's capacity to intervene in the foreign exchange market to stabilise the exchange rate during period of extreme volatility. In addition, given that exchange rate volatility was comparably more extreme following the post poll crisis in 2008; political stability is a key component of foreign exchange market stability in Kenya.

LIMITATIONS AND SUGGESTIONS

Given the importance of the Euro, Sterling Pound and Japanese Yen in the Kenyan economy, it may be of interest to replicate this study considering exchange rate returns of the Kenya Shilling against these international currencies. The study can also be extended to incorporate other variations of the GARCH model to generate the volatility process.

Conflict of Interests

The authors have not declared any conflict of interest.

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REFERENCES

Andreev OV, Tinykov ES, Ovchinnikova PO, Parahin PG (2012). "Extreme Value Theory and Peaks Over Threshold Model in the Russian Stock Market." Journal of Siberian Federal University, Engineering and Technologies 1(5):111-121.

Bollerslav T (1986). "Generalised Autoregressive Conditional Heteroscedasticity." J Econom. 31: 307-27.

Bollerslav T, Chou RY, Kroner KF (1992). "ARCH Modeling in Finance, A Review of the Theory and Empirical Evidence." J. Econom. 52:5-59.

Becketti S, Sellon GH (1989). "Has Financial Market Volatility Increased? Federal Reserve Bank of Kansas City". Economic Review Journal. 17-30.

Central Bank of Kenya (2008). Monetary Policy Committee Report, October 2008.

Central Bank of Kenya (2009). Annual Report, 2009.

Central Bank of Kenya (2012). Monetary Policy Committee Report, April 2012.

Central Bank of Kenya (2013). Monetary Policy Committee Report, October 2013.

Embrechts P, Kluppelberg C, Mikosch T (1997). Modelling Extremal Events, Springer, Berlin.

Engle FR (1982). "Autoregressive Conditonal Heteroscedasticity with Estimates of Variance of United Kingdom Inflation". Econometrica 50:987-1008.

Floros C (2008). "Modelling Volatility using GARCH models: evidence from Egypt and Israel". Middle Eastern Finance Econ. 2:31-41. ISSN 1450-2889.

Franke J, Härdle WK, Hafner CM (2008). Statistics of Financial Markets, An Introduction, Second Edition, Springer.

Jarque CM, Bera AK (1987). "A test of Normality of Observations and regression Residuals". International Statistical Review. 55:163-172.

Kenya National Bureau of Statistics (2014). Economic Survey 2014.

McNeil A (1997). "Estimating the Tails of Loss Severity Distributions Using Extreme Value Theory". ASTIN Bulletin 27:117-137.

McNeil A, Frey R (2000). "Estimation of tail- related risk measures for heteroscedastic financial time series: an extreme value approach". J. Empir. Financ. 7:271-300.

Nelson D (1990). "Stationarity and Persistence in the GARCH (1, 1) model". Economet. Theory 6:318-334.

Republic of Kenya (2007). Kenya Vision 2030, Nairobi: Government Press.

Resnick S, Starica C (1996). "Tail Index Estimation for Dependent Data". School of ORIE, Cornell University, Discussion Paper.

Smith RL (2003). "Statistics of extremes, with applications in environment, insurance and finance". Chappel Hill. North Carolina: University of North Carolina, Department of Statistics.

Tsay RT (2005). Analysis of Financial Time Series. Second Edition. Wiley Series in Probability and Statistics.

Appendix 1. Selected Statistics for Daily Exchange Rates of the Kenya Shilling against the U.S. dollar.

Year	Mean	Standard deviation	Minimum	Maximum
1999	70.44	5.17	61.31	77.07
2000	76.19	2.59	67.46	79.76
2001	78.57	0.53	77.28	79.93
2002	78.72	0.53	77.07	80.28
2003	75.94	1.96	66.04	79.19
2004	79.17	1.82	75.94	82.52
2005	75.57	1.48	72.09	78.93
2006	72.15	1.11	69.21	74.48
2007	67.42	1.76	61.77	70.63
2008	69.05	5.75	61.51	80.12
2009	77.34	1.90	74.33	81.11
2010	79.26	1.99	75.36	82.10
2011	**88.87**	**6.18**	**80.74**	**105.96**
2012	84.52	1.18	82.27	88.44
2013	86.13	1.21	83.72	87.70

Annual means, standard deviation, minimum and maximum statistics for the exchange rate of the Kenya Shilling to the U.S. dollar.

Appendix 2. Correlogram of Squared Exchange Rate Returns of Kenya Shilling against the U.S. dollar.

Lag	Autocorrelation Coefficient	Partial Autocorrelation Coefficient	Q-Stat	Prob
1	0.3300	0.3300	408.4000	0.0000
2	0.3470	0.2680	861.4300	0.0000
3	0.2390	0.0810	1075.9000	0.0000
4	0.2280	0.0770	1271.8000	0.0000
5	0.1900	0.0480	1407.9000	0.0000
6	0.1000	-0.0530	1445.5000	0.0000
7	0.1070	0.0090	1488.3000	0.0000
8	0.0690	-0.0040	1505.9000	0.0000
9	0.0890	0.0340	1535.8000	0.0000
10	0.0900	0.0440	1566.2000	0.0000
11	0.0780	0.0180	1589.1000	0.0000
12	0.0900	0.0280	1619.3000	0.0000
13	0.1140	0.0580	1668.1000	0.0000
14	0.1390	0.0640	1741.0000	0.0000
15	0.1340	0.0370	1808.9000	0.0000
16	0.1090	-0.0030	1853.7000	0.0000
17	0.1090	0.0070	1898.3000	0.0000
18	0.0890	-0.0060	1928.4000	0.0000
19	0.1070	0.0290	1971.3000	0.0000
20	0.0800	0.0050	1995.5000	0.0000

Appendix 3. Correlogram of Squared Standardised Residuals from GARCH (1, 1) Model.

Lag	AC	PAC	Q-Stat	Prob
1	0.0020	0.0020	0.0202	0.8870
2	-0.0100	-0.0100	0.4277	0.8070
3	-0.0150	-0.0150	1.2545	0.7400
4	-0.0100	-0.0100	1.6627	0.7970
5	-0.0100	-0.0100	2.0312	0.8450
6	-0.0160	-0.0160	2.9683	0.8130
7	-0.0090	-0.0090	3.2505	0.8610
8	-0.0060	-0.0070	3.4013	0.9070
9	0.0250	0.0240	5.7426	0.7650
10	-0.0080	-0.0090	5.9834	0.8170
11	-0.0070	-0.0070	6.1546	0.8630
12	-0.0080	-0.0080	6.3848	0.8950
13	-0.0090	-0.0100	6.7206	0.9160
14	-0.0060	-0.0060	6.8528	0.9400
15	-0.0100	-0.0100	7.2248	0.9510
16	-0.0070	-0.0070	7.4033	0.9650
17	0.0140	0.0130	8.1063	0.9640
18	0.0000	-0.0020	8.1066	0.9770
19	0.0090	0.0090	8.4054	0.9820
20	0.0060	0.0060	8.5565	0.9870

[i] The views expressed in this paper are the authors' and do not necessarily reflect those of the Central Bank of Kenya.
ii The nominal GDP data used in the computation is based on the rebased GDP series released in September 2014).

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Effects of credit constraints on the productivity of small and medium-sized enterprises in Cameroon

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This paper assesses the determinants and effects of credit constraints on the productivity of small and medium-sized enterprises (SMEs) in Cameroon. Use is made of the Cameroon enterprise survey data collected by the World Bank in 2009 and an endogenous switching regression model. Results show that interest rates, size of enterprise, size of loan, size of collateral, maturity of loans and legal status of enterprises are major sources of credit constraints faced by SMEs. Results also indicate that medium enterprises are more credit constrained than small enterprises; meanwhile the effects of credit constraints affect small enterprises more than medium enterprises. Credit constrained firms have lower levels of productivity relative to unconstrained firms. These results have implications for the creation of credit bureaux, prudential stringency and rationalization of the Cameroon tax system.

Key words: Small and medium-sized enterprises, credit constraints, endogenous switching regression model, Cameroon tax system.

INTRODUCTION

The recent enterprise survey conducted by the National Institute of Statistics (NIS) (NIS, 2009) reveals that there are 93 969 enterprises in Cameroon out of which 99.2% are small and medium-sized enterprises (SMEs).They account for 62% of permanent employees and 31% of turnover before tax of all enterprises in Cameroon (NIS, 2009).The importance of SMEs has been underlined as a focal point of the vision 2035 of the 2009 growth and employment strategy paper (GESP) of the government of Cameroon (Government of Cameroon, 2009). The creation of the Ministry of Small and Medium-sized Enterprises, Social Economy and Handicraft in December 2004 is an indicator of the importance of this sector to the economy of Cameroon.

In general, SMEs have been reporting difficulties in financing their activities (Beck, 2004; Slotty, 2009).The enterprise survey(World Bank/IFC, 2008) shows that 51% of small enterprises (5-20 employees) and 45% of medium enterprises (21-99 employees) in sub-Saharan Africa consider access to finance as their major obstacle and this reduces with size. The same survey also indicates that only 38% of big (100 and more employees) enterprises mention access to finance as their major obstacle. Results from a survey carried out by NIS in 2009 shows that 37.6 % of the SMEs in Cameroon have problems of access to credit (NIS, 2009). The 2009 and 2010 Doing Business reports show that enterprises in Cameroon passed from 131st position in 2009 to 135th in

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2010 as far as access to credit is concerned (World Bank, 2010).

Apart from the problem of financing SMEs, bad business environment has been identified as one of the main predicaments to their development. The business environment in Cameroon is characterised by corruption, long administrative procedures, insufficient or lack of infrastructures like roads, electricity, poor legal system and very high transaction costs and custom duties at the ports of shipment. These problems force SMEs to use inappropriate methods of production or out-dated technology (NIS, 2009).The problem of access to credit has always been and remains a major drawback for the growth of SMEs in Cameroon (Berk et al., 2006). The government of Cameroon recently created a bank for financing SMEs. Although this bank is still in the process of implantation, it may respond to the important constraints that SMEs face in financing their activities only if the general business environment is improved.

Despite the important role of SMEs in the economies of the developing world as one of the major employers with very high contribution to GDP, recent research provide evidence that SMEs face greater financing obstacles than large firms (Beck et al., 2005; Beck and Demirgüç-Kunt, 2006; and Beck et al., 2006). Ayyagari et al. (2007) show that finance, crime, and political instability directly affect the rate of growth of firms, with finance being the most robust variable affecting firms' growth rate. Access to credit by SMEs is extremely limited. Banking penetration of the private sector is very low in Cameroon; it is only averaging 18% of GDP (World Bank, 2006) and it is only major corporations or big enterprises that benefit from the bulk of financing.

This paper outlines the principal credit constraints faced by SMEs and analyses the effects of credit constraints on the productivity of credit constrained and unconstrained firms in Cameroon. In this context, this paper makes a contribution by extending knowledge on credit constraints in Cameroon and empirically evaluating the impact of credit constraints on the productivity of SMEs. The rest of the paper is structured as follows: Section II summarizes recent literature on credit constraints faced by SMEs, section III dwells on the methodology; while Section IV presents the results and discussions.

LITERATURE REVIEW

A model of imperfect information, uncertainty and credit rationing was published by Dwight and Russell (1976). It is assumed in this model that there are both ″honest″ and ″dishonest″ borrowers. Honest borrowers are those that accept loan contracts they are sure they would repay on time; while dishonest borrowers are those that accept loan contracts they know they won't be able to repay on time. The model shows that the loan market is composed of borrowers who detain more information about their likelihood of default than the lenders. In the case of a perfect competition market there are two cases, in the first case; borrowers are rationed in the amounts they can repay so there is no default. In the alternative case, the market can alternate in an unstable fashion with lenders entering and making short-run profits and then disappearing in the long-run. In reality loan markets may not exhibit any of these features. Although bank failures may absorb a percentage of the default, the market does not show instability as predicted by the model. Entry into the loan market entails non-price terms such as collateral, and down payment requirements. Government intervention may also be justified as one of the solutions to market failures. Changes in the legal system may equally correct bank failures.

The credit and financial markets are considered in institutional economics as institutional structures and arrangements that can mediate the exchange process and minimise transaction costs. The nature of costs is very important because it determines the structure of the market (Saleh, 2004). For example; in a country where transaction costs are relatively low, borrowers would be able to finance their projects with bank loans instead of their small savings or ask for help from friends or family. It is important to bear in mind that these costs are generally a function of factors such as uncertainty, structure of the market, economic rationality and the ability of agents to access opportunities. Consequently, in a situation of uncertainty like that which characterises the credit market in Cameroon, it is difficult or expensive to negotiate credit contracts that take into consideration all the above exigencies. In addition, the fact that this market is dominated by some banks limits competition thus giving them market power that can influence the cost of transactions.

Due to information asymmetry, external funds are imperfect substitutes of internal funds (Braun and Larrain, 2003). Thus, enterprises with higher cost of information are more likely to be credit constrained. Empirically the credit constrained statuses of SMEs are generally identified by their sensibility to investment (Bönte and Nielen, 2010). The principle behind this reasoning is that due to credit constraints external funds are more expensive than internal funds.

The development of the financial system has also been used as an important tool to determine the vulnerability of SMEs to be credit constraint (Laeven, 2003). Better protection of property rights increases external financing of small firms significantly more than it does for large firms, particularly due to the differential impact it has on bank and supplier finance (Beck et al. 2004). Beck et al. (2005) show that the effect of obstacles on firm growth is smaller in countries with better-developed financial and legal systems. Using cross-industry, cross-country data for 44 countries and 36 industries in the manufacturing sector, Beck et al. (2005) show that financial development exerts a disproportionately large positive effect on the growth of industries that are naturally composed of more small firms. Their results suggest that the furniture industry (an industry with many small firms) should grow 1.4% per annum faster than the spinning industry (an industry with relatively fewer small firms) in Canada (a country with a well-developed financial system) than in India (which has a lower level of financial development).

Mina et al. (2011) developed a model with inspiration from that of Brixiova and Kiyotaki (1997) which is based on the situation prevalent in African economies where SMEs are credit constrained and are limited by lack of collateral. The model is applied to African countries where formal and productive private sector is under-developed. The empirical implementation was based on panel data involving 20 African countries. The results from the study show that new enterprises are considered as risky. It also highlights the importance of the legal system in reducing information asymmetry and enforcing credit contracts, which is still a big problem in Africa. The lack of competition is also identified as one of the factors leading to limited access to credit by SMEs, engendering high collateral demands. Due to this, we have the cohabitation of excess liquidity and credit constraints, thus interventions aimed at reducing cost of credit and strengthening of the legal system are required (Calvin, 2008).

Tieguhong et al. (2012) highlighted the problem faced by SMEs through an analysis of the financial gap of 151 pilot enterprises (63 in Cameroon and 88 in the Democratic Republic of Congo, DRC). The total capital required for the development of these 151 pilot enterprises was evaluated at US$1 335 025 out of which the own contribution of the enterprises was US$ 843 433 (63%) and the other US$ 492 159 (37%) was subject to external assistance. They also found that there was consistent variation in capital requirements, own contributions and levels of assistance sought among the enterprises. The research also shows that the level of assistance sought in Cameroon is less than that in the DRC.

Ngoa and Niyonsaba (2012) used a multinomial logit model to verify the impact of entrepreneurial social capital on the credit access of SMEs in Cameroon. A sample of 413 Cameroonian SMEs where questioned and five indicators where used; the ratio of family labour, government support, belonging to a business network, personal relation with the client bank and the level of human capital predominant in the enterprise. The results show that only the three last variables positively affect access to bank credit. However, their effects and amplitudes vary with respect to the maturity of the loan.

The study also shows that thanks to social capital, SMEs that have access to bank credit survive for a longer period than the others. The present paper contributes to a better understanding of the impact of credit constraints on the productivity of SMEs in Cameroon.

DATA AND METHODOLOGY

Data

The dataset used in this study is secondary data from the World Bank 2009 enterprise survey in Cameroon. The enterprise survey aims at factors that shape the business environment of the economy. It examines the accommodating and constraining factors to enterprise growth. The accommodating factors are those that contribute to the growth and productivity of the enterprise and also the economy. Meanwhile, constraining factors are obstacles to sustainable development and growth of enterprises.

The enterprise survey covers small, medium and large firms. The survey is administered to representative firms of the non-agricultural formal private economy. It includes the manufacturing sector, service sector, and transport and construction sectors. Public utilities, health care, government services and financial sectors are not included in the sample. A wide variety of quantitative and qualitative information was collected in Cameroon through face to face interviews with firm managers and owners on diverse topics; infrastructure, trade, finance, regulations, taxes, business licensing, corruption, crime, informality, innovation, labour and perceptions about obstacles to doing business in Cameroon.

In Cameroon, business owners and managers of 363 firms were interviewed from April through October 2009. The survey was carried out in 03 main towns in Cameroon: Douala, Yaoundé and Bafoussam. The enterprise survey was organised in two stages, in the first stage a telephone screening was organised to confirm eligibility and to schedule an interview. In the second stage, a face to face interview with a top manager of the firm was conducted. When needed, follow-up questions and corrections were implemented in person, by phone, through emails or web interface.

Methodology

In this research, the definition of credit constrained firm follows from Casey and O'Toole (2013). In this regard, a SME is said to be credit constrained if it requested more loans than was supplied, did not apply for a loan because of unfavourable credit conditions or if it required loans but was unable to borrow. When estimating the impact of credit constraints on productivity, two issues come up (Maddala, 1986). The first step to estimate SMEs credit constraints is by a probit function with the following specification:

$$\mathrm{C_i}^* = \alpha Z_i + \mathrm{u}_i > 0 \tag{1}$$

where C* is a latent continuous variable, which determines the credit constraint status of a SMEs. It takes two values;

$\mathrm{C_i} = 1 \text{ if } \mathrm{C_i}^* > 0$ (credit constraint)

$\mathrm{C_i} = 0 \text{ if } \mathrm{C_i}^* \leq 0$(credit unconstraint)

The SME credit constraint criterion equation is a reduced form equation, i.e. the condition of whether a SME is credit constrained or unconstrained, and is given by an index model, $\mathrm{C_i}^*$ which is a latent variable that cannot be observed but can be estimated via assumptions on how it is characterized, $\mathrm{Z_i}$ represents a vector of explanatory variables, α is a vector of parameters to be estimated and $\mathrm{u_i}$ is a random error term, distributed as a normal function with mean zero and the variance normalised to one in order to allow for estimation of coefficients. Finally SME productivity equation is estimated by the following regression equation; regime 1 represents credit constrained SMEs and regime 0 represents unconstrained SMEs.

Productivity of credit constrained SMEs is given as equation 2:

$$Y_{1i} = \beta_1 X_1 + \varepsilon_{1i} \text{ if } C_i = 1 \quad (2)$$

Productivity of credit unconstrained SMEs is given as equation 3:

$$Y_{0i} = \beta_0 X_0 + \varepsilon_{0i} \text{ if } C_0 = 0 \quad (3)$$

Where Y_{1i} and Y_{0i} are the productivity for credit constrained and unconstrained SMEs, X_1 and $X_0$are vectors of the explanatory variables for credit constrained and unconstrained SMEs respectively, while $\beta_1$and β_0 are vector of corresponding parameters to be estimated. The terms ε_{1i} and ε_{0i} are random error terms, distributed as normal function with zero means.

As demonstrated in Maddala (1983), the expected value of the error terms ε_{1i} and ε_{0i} are not zero. This is because the counterfactual productivity that credit constrained SMEs would have had without being constrained is not observed. In addition, we do not observed the productivity that SMEs that are not credit constrained would have had if they were constrained. If we could estimate such counterfactuals, this problem could be solved. This is known as the sample selectivity problem and is well known in economic literature (Heckman, 1979; Puhani, 2000; Lung-Fei, 2001). This makes direct OLS estimation of equations (2) and (3) inappropriate. In this study, a strategy developed by labour economists is adopted; mostly by Heckman (1979).This problem is addressed by calculating the inverse Mills ratio from equation (1), and inserted as explanatory variables in (2) and (3). The second problem with this model is that the annual sales revenues (productivity) of SMEs depend on the credit equation criterion and also on other characteristics of the SMEs. Therefore, the errors of the credit constraint criteria are correlated with that of the productivity of credit constrained SMEs and unconstrained SMEs. Thus, there is a problem of endogeneity. Due to these issues, the OLS method is inappropriate to estimate the coefficients; the maximum likelihood method is used. To achieve this, stata movestay command is used, which uses the maximum likelihood function to estimate the coefficients and does a joint estimation of a probit model for the credit constraint status equation and the regression equations of regime 1 and regime 0 respectively.

In order to capture the unobserved characteristics of SMEs that affect productivity, the inverse Mills ratio is introduced in the expected SME productivity. The expected productivity of SMEs conditional to credit constrained regime can be computed as;

$$\begin{aligned} E[\tfrac{y_{1i}}{x_i}, C_i = 1] &= E[\tfrac{y_{1i}}{x_i}, \alpha_{zi} + \mu_i > 0] \\ &= \beta_1 x_1 + E\left[\tfrac{\varepsilon_{1i}}{\mu_i}\right] > -\alpha z \quad (4a) \\ &= \beta_1 x_1 + (\sigma_1 \sigma_\mu \rho_1)[\emptyset \tfrac{\alpha_{zi}}{\Phi(\alpha z_i)}] \end{aligned}$$

In the same way, the expected SME productivity, unconditional to the constrained regime is given by;

$$\begin{aligned} E[\tfrac{y_{0i}}{x_i}, C_i = 0] &= E[\tfrac{y_{0i}}{x_i}, \alpha z_i + \mu_i < 0] \\ &= \beta_0 x_0 + E[\varepsilon_{0i}/\mu_i > \alpha z] \quad (4b) \\ &= \beta_0 x_0 + (\sigma_0 \sigma_\mu \rho_0)[-\emptyset \tfrac{\alpha z_i}{(1-\Phi(\alpha z_i))}] \end{aligned}$$

Where y is the SME productivity, X_1 and $X_0$are vectors of the explanatory variables for credit constrained and unconstrained SMEs respectively, while β is a vector of corresponding parameters to be estimated. The terms ε_{1i} and ε_{0i} are random error terms, distributed as normal function with zero means. The terms ∅ and Φ are the probability density function and the cumulative distribution function of the standard normal distribution, respectively. According to Greene (2003), the ratio ∅ and Φ evaluated at αz is the inverse Miller ratio (λ). This reflects the truncation of a normal distribution atα'z.

$\lambda_1 = [\emptyset \frac{\alpha z}{\Phi(\alpha z)})]$ and $\lambda_0 = [-\emptyset \frac{\alpha z}{(1-\Phi(\alpha z))})]$ could be added to the X_1 and X_0 vectors respectively in equation (5a) and (5b) to yield:

$$E[\tfrac{y_{1i}}{x_i}, C_i = 1] = \beta_1 x_1 + (\sigma_1 \sigma_\mu \rho_1)\lambda_1 + \eta_{1i} \quad (5a)$$

$$E[\tfrac{y_{0i}}{x_i}, C_i = 0] = \beta_0 x_0 + (\sigma_0 \sigma_\mu \rho_0)\lambda_0 + \eta_{0i} \quad (5b)$$

The covariance of the credit constrained criterion equation (1), and the credit constrained SMEs productivity equation (5a),and the credit unconstrained criterion equation (1), and the credit constrained SMEs productivity equation (5b) are represented by the multiplicative terms $\sigma_1 \sigma_\mu \rho_1$and $\sigma_0 \sigma_\mu \rho_0$, respectively. This covariance can be split into the standard deviation of the appropriate equations $\sigma_\mu \sigma_1 \sigma_0$ and the correlations $\rho_1$andρ_0. However σ_μ cannot be estimated and is normalise to 1 because of the structure of the model and the nature of the derived data (Greene, 2003).

To measure the endogeneity of the credit constrained condition, a test of whether ρ_1 and ρ_0 are statistically different from zero is required, since estimates of ρ_1 and $\rho_0$show correlation of the "unobservable" of the credit constrained criterion equation with the "observables" of the credit constrained and unconstrained SME productivity equations, respectively. If ρ_1 and ρ_0 are zero then the credit constraint is exogenous, and it would be necessary to include the credit constrained criterion equation in estimating the effects of credit constraints on the productivity of SMEs.

This system can be estimated in two steps. The two steps approach required the estimation of probit function (1), which is first estimated by maximum likelihood. The predicted values from the probit function are then used to calculate the inverse Mills ratio, which is subsequently included as an explanatory variable when estimating equation (5a) and (5b). A single parameter is estimated for $\sigma_1\rho_1$ and $\sigma_0\rho_0$ because of the linear structure of these equations. The one-step approach (endogenous switching regression model) entails the estimation of β_1,β_0 and α for starting values equations (1),(5a) and (5b) jointly by maximum likelihood. With the maximum likelihood estimation (MLE) equation, separate estimates of ρ_1 and σ_1 and then ρ_0 and σ_0 are possible. In a nutshell, the endogenous switching model is implemented in two stages. In the first stage, a probit model is estimated to detect enterprises that are credit constrained, while in the second stage, simultaneous equations are used to estimate productivity of constrained enterprises compared to unconstrained enterprises. This implies two dependent variables, one at each stage. From the above we can specify two hypotheses;

• Non-credit constrained SMEs outperform their credit constrained counterparts

Table 1. Variables selected for study.

Variable	Nature	Expected sign (positive(+), negative (-))	Description
Access to credit (cc)	Dependent		1 if credit non constrained (have a line of credit or a loan or does or has enough funds and 0 otherwise (loan application rejected or did not apply because of long procedures to get a loan, high interest rate, high collateral demands, size and maturity of loan insufficient, did not think it would be approved)
Log of annual sales(sales)	Dependent		It evaluates the productivity of SMEs
Size of Enterprise	Independent	Small(+) Medium (+) Large(-)	Dummy variable (1=yes and 0=no) • Small • Medium • Large
Current legal status	Independent	Sole proprietor(-) Partnership (+) Limited partnership (-)	Dummy variable : (1=yes and 0=no) • Sole proprietor • Partnership • Limited partnership
Top female manager	Independent	+	1= yes and 0=no
Average interest rate	Independent	-	It is the rate charged by banks when you borrow.
Size of Collateral	Independent	+	It is the log of the value of collateral
Credit history	Independent	+	1 if the enterprise had applied for a loan before and 0 if not
Age of the enterprise	Independent	-	It is counted from 2009 minus the year it was officially registered
Bank account	Independent	-	1= yes and 0=no
Existing assets	Independent	-	1= yes and 0=no

Source: Compiled by authors.

• Credit constrains have significant negative effects on the productivity of SMEs

Presentation of variables

The two endogenous variables are access to credit and productivity.

Access to credit (cc): it is a variable which is used to estimate the probability of an enterprise being credit constrained or unconstrained. It is a binary variable with outcome zero or one

Productivity (log annual sales): it is a variable that is used to evaluate the performance of credit constrained and unconstrained enterprises. It is a continuous variable. The variables of interest are summarized in Table 1.

EMPIRICAL RESULTS

Determinants of SMEs credit constraints in Cameroon

The results in Table 2 below shows that the probability of being credit constraint increases with increase in size of enterprises. This can be seen by higher positive value of the coefficient of small and medium enterprises; these coefficients are significant at 10% and 5% levels, respectively. This phenomenon contradicts the findings of Beck et al.(2005) and Beck et al.(2006) that Small firms face greater financing obstacles than medium-sized firms. This is mainly because many small enterprises easily get loans from credit unions and microfinance institutions because of their personal relationship with the microfinance operators. The manager of the microfinance knows the owners of the small enterprises in person, their houses and the location of their business centers. This makes it easier to give out loans to small enterprises, this confirms the findings of Ngoa and Niyonsaba (2012) where there was a positive and significant impact of relationship with bank on credit access in Cameroon, and small enterprises typically lack the capacity to deal with commercial banks. Another reason is the over liquidity phenomenon in the CEMAC region where banks receive short-term deposits and consequently cannot give out

Table 2. Probit regression estimates of determinants of SMEs credit constraints condition: endogenous switching regression -part 1.

Variable	Coefficient	Standard error	t-statistics
Size of Enterprise			
Small	0.823166*	0.4358359	1.89
Medium	0.9803419**	0.4752202	2.06
Legal status of Enterprise			
Sole proprietorship	-1.150219***	0.3602106	-3.19
Partnership	-0.7260604	0.4527223	-1.60
Limited partnership	1.82318	1.430684	1.27
Experience of top manager	-0.0029877	0.0164781	-0.18
Interest rate	0.1541037***	0.0282023	5.46
Age of enterprise	0.007695	0.0113611	0.68
Size of loan	0.1439886***	0.0274468	5.25
Size of collateral	-0.0167842	0.0217931	-0.77
Credit history/relationship with bank	2.01287***	0.4348153	4.63
Existence of fixed assets	-0.6887105***	0.2996057	-2.30
Have saving account	-0.1153333	0.4613401	-0.25
Top manager female	1.092383***	0.4519805	2.42
Constant	-3.765733***	0.7713068	-4.88

Notes:***, **, and * denote significance of estimated coefficient at 1, 5, 10 percent levels of probability respectively. Source: By the author using the switching regression technique SMEs survey in stata SMEs data collected by the world bank. Number of obs = 363; Number of obs = 363; Wald chi2(8) = 60.67; Prob> chi2 = 0.0000; Log likelihood = -813.12613 ; LR test of indep. eqns. : chi2(1) = 13.74 Prob> chi2 = 0.0002.

long-term loans. In this regard, only small enterprises that demand short-term loans at higher interest rates can have access to credit, making medium enterprises to be more credit constrained.

As far as the legal status of the enterprise is concerned, the probability of being credit constrained significantly decreases for sole proprietors at the 1% level. This is principally because sole proprietors have personal relationships with their microfinance or credit union institutions so the problem of information asymmetry is highly reduced and they usually demand short-term loans. Partnerships have lower risk while limited partners have a positive non-significant relationship with the probability of being credit constrained.

The probability of an enterprise being credit constrained increases with interest rate. This is to be expected because it is the price which borrowers have to pay for the credit. Some enterprises may not apply for a loan because they feel the interest rate is too high, not because they have sufficient funds. It is also used by banks as a measure to cover other costs of obtaining information, especially in an economy like that of Cameroon with high information asymmetry (Williamson, 1987).

The age of an enterprise has a positive non-significant relation with the probability of a SME being credit constrained. That is, the age of older SMEs have very little or no influence on the probability of being credit constrained.

The bigger the size of the loan demanded by enterprises the higher the probability of the SMEs being credit constrained. Indeed, the effect of bigger loans may increase the probability of an enterprise being credit constrained by about 14%. This is because bigger loans are likely to require bigger collateral or the maturity period demanded by the borrower may be longer. This contrasts with the vision of most banks that are more willing to give out short-term loans.

Collateral is often demanded as one of the alternative measures by banks to reduce the risk of default by borrowers. The size of this collateral (Table 2) is negatively related to the probability of the enterprise being credit constraint. Some enterprises may not be awarded the loan they demanded or only awarded a partial amount because they do not have the required collateral. Some SMEs may just decide not to apply for a loan or line of credit because they feel the collateral needs are prohibited for them. So the higher the value of the collateral, the lower the probability of being credit constrained.

When enterprises have fixed assets the probability of those enterprises being credit constrained is reduced. This is so because the enterprises have assets that can be presented as collateral. Thus, an enterprise can borrow more when she possesses substantial collateral. This is a great cover for the enterprises because it is an assurance to the banker that the loan would be paid even if it means selling the collateral. From our results, the probability of a SME being credit constrained reduces by 68% when the SME have fixed assets. This variable is significant at the 1% level.

Having a bank account by a SME is an important step towards obtaining loans or lines of credit from financial institutions. This variable is negatively related to the credit constrained condition of SMEs.

Access to credit is highly gender sensitive. Enterprises with women top managers increase their probability of being credit constrained - coefficient is significant at 1% level. Female managers in Cameroon still do not have the same rating as men to the extent that bankers find it easier to give out loan to a male top manager rather than a female manager.

Effects of credit constraints on the productivity of SMEs in Cameroon

The log of annual sales revenue is used as an indicator of the productivity of SMEs it models the probability of a variable increasing or reducing sales revenue with respect to the credit constraint status of the firm. The results of the effects of credit constraints on the productivity of SMEs can be seen in Table 3.

Credit constrained equation

The first panel of Table 3 shows that small- and medium-size enterprises have negative and significant effects on sales revenue, but the absolute magnitude of the coefficient on small enterprises larger than that of medium-sized firms. This means that credit constrained small and medium firms have lower annual sales revenue, but that of small enterprises is much lower than that of medium-sized enterprises. Thus, the consequence of credit constraints is more for small firms than for medium firms.

As far as the legal status of SMEs is concerned, partnerships, sole proprietors and limited partners all have a negative and significant effect on annual sales revenue. However, this is larger (by 0.64) for sole proprietors compared to partners, while limited partners have the lowest negative value. The implication is that sole proprietors and partners are highly touched by the credit constrained status than limited partners.

The experience of the manager has a positive effect on the annual sales revenue of SMEs. There is a 2% increase in sales revenue due to a unit increase in the experience of the manager. Interest rates have negative and significant effects on the annual sales revenue of enterprises. This means that an increase in the interest rate for credit constrained firms reduces their productivity.

The credit unconstrained equation

The second panel of Table 3 shows the estimated results of the credit unconstrained firms when the log of annual sales is the dependent variable. As far as the size (small, medium, large) of SMEs are concerned, they all have negative and significant effects on the annual sales revenue. Small firms have a higher negative (0.51) effect than medium firms. This means that even when firms are not credit constrained, small firms record lower annual sales revenue compared to medium firms while the coefficients for credit constraints firms is much lower.

Limited partners have a positive and significant effect on annual sales revenue, while partners and sole proprietors have negative effects on annual sales revenue.

At the level of management of the enterprise, the experience of the top manager has a positive and significant effect at 10% level on sales revenue. Sales revenue tends to increase by 2.5% with a year increase in experience of the top manager

The correlation coefficients rho_1 indicates the correlation between the credits constrained situation and the effects of credit constraints on credit constrained firms. The value is negative and statistically significant. The value is 0.82, which is a very strong correlation, meaning that being credit constrained has significant adverse effects on sales revenue (Table 3). Thus, sales revenue tends to reduce because of credit constraints.

The correlation coefficients rho_2 indicates the correlation between the credits constrained situation and the effects of credit constraints on credit unconstrained firms. The value is negative but it is only significant at the 10% level. The value is 0.43, reflecting a weak correlation. Therefore, credit unconstrained firms turn to have higher annual sales revenue compared to credit constrained firms, which confirms the observation that credit constraints have significant negative effects on the productivity of SMEs. These results show that credit constraint is endogenous and thus it is necessary to model the credit constraint criterion equation in estimating the effects of credit constraints on the productivity of SMEs.

Concluding remarks

This paper outlined the important role that the size of collaterals may have on the probability of a firm being credit constraint. The probit regression showed that when the size of the collateral is large the probability of SMEs being credit constrained is reduced by 1.6%. Thus, having collateral in Cameroon is a good guarantee to secure credit from a microfinance institution. On the other hand, having fixed assets is a big guarantee to have a loan in Cameroon; the probability of credit constraints reduces by 68.87%. Size of loan and interest rate are the principal elements which increase the probability of enterprises being credit constraints; they increase this probability by 14.39 and 13.41% respectively.

Table 3. Effects of credit constraint on productivity of SME, estimated by maximum likelihood switching regression - switching regression (part 2).

Variable	Coefficient	Standard error	t-statistics
Credit constrained equation			
Size of Enterprise			
Small	-2.575423 ***	0.5373712	-4.79
Medium	-1.175191***	0.488681	-2.40
Legal status of Enterprise			
Sole proprietorship	-1.185184 ***	0.4577519	-2.59
Partnership	-2.233041***	0.6799892	-3.28
Limited partnership	-0.4192783	0.8429436	-0.50
Experience of top manager	0.0212495	0.0209463	1.01
Interest rate	-0.0847042***	0.035304	-2.40
Top female manager	-1.249014	1.000087	-1.25
Constant	22.50572***	0.7806397	28.83
Credit unconstrained equation			
Size of Enterprise			
Small	-2.18498 ***	0.372059	-5.87
Medium	-1.670859***	0.3736549	-4.47
Legal status of Enterprise			
Sole proprietorship	-1.150219***	0.3602106	-3.19
Partnership	-0.510959	0.4795876	-1.07
Limited partnership	1.556253	1.978229	0.79
Experience of top manager	.0252573*	0.0143036	1.77
Top female manager	-0.5175267	-0.5175267	-1.37
Constant	20.01186 ***	0.4594352	43.56
/lns1	0.7837656 ***	.0757205	10.35
/lns2	0.6761087***	.0467539	14.46
|r1	-1.180721 ***	0.5467111	-2.16
r2	-0.4719994	0.3090944	-1.53
sigma_1	2.189702	.1658053	
sigma_2	1.966212	0.091928	
rho_1	-0.8276789	0.1721854	
rho_2	-0.4398134	.2493045	

Notes: ***, **, and * denote significance of estimated coefficient at 1, 5, 10 percent levels of probability respectively. Source: By the author using the switching regression technique SMEs survey in stata SMEs data collected by the World Bank. Number of obs = 363; Wald chi2 (8) = 60.67; Prob> chi2 = 0.0000; Log likelihood = -813.12613; LR test of indep. eqns. : chi2(1) = 13.74 Prob> chi2 = 0.0002.

The effects of credit constraints on the productivity of SMEs was captured by the coefficients of the variables, but the correlation coefficients rho_1 and rho_2 gave the global effects of credit constraints on SMEs. The correlation coefficient, rho_1, indicates the correlation between the credits constrained equation and the effects of credit constraints on credit constrained firms. The value was negative and statistically significant indicating a strong correlation between the two models. The implication is that being credit constrained has significant adverse effects on sales revenue, thus sales revenue tends to reduce because of credit constraints. Therefore, credit constrained firms would turn to have lower sales revenue compared to their credit unconstrained counterparts.

These findings have implication for increasing SMEs access to credit by reducing information asymmetry and strengthening prudential stringency. For example, the government of Cameroon could accompany the creation of the public bank for SMEs, with an effective credit registry bureau, which indicates firms listed in the private or public domain together with their credit histories.

Financial institutions could, then, be given the permission to easily access this information. This would reduce information asymmetry and enable the banks to be able to give out loans to SMEs that do not have huge collaterals or at lower interest rates subject to stringent regional prudential controls. It would encourage loans of higher value to be given out for investment to qualified SMEs and also increase employment opportunities.

Conflict of Interests

The authors have not declared any conflict of interest.

REFERENCES

Ayyagari M, Beck T, Demirguc-Kunt A (2007). “Small and Medium Enterprises Across the Globe”, Small Bus. Econ. 29:415–434.

Beck T, Demirguc-Kunt A (2006). “Small and medium-size enterprises: Access to finance as a growth constraint”, J Bank Financ. 30:2931-2943.

Beck, T, Demirguc-Kunt A, Maksimovic V (2005). “Financial and Legal Constraints to Firm Growth: Does Size Matter?” J. Financ. 60(1):137–177.

Beck T, Demirgüç-Kunt A, etMaksimovic V (2006). “The Determinants of Financing Obstacles”, J. Money Financ. 25:932-952.

Beck T, Demirgüç-Kunt A, Levine R (2005). SMEs, Growth, and Poverty: Cross-Country Evidence, J Econ. Growth 10:197-227.

Beck T, Demirgüç-Kunt A, Maksimovic V (2004b). “Bank Competition and Access to Finance: International Evidence,” J. Money Credit Bank 36(3):627-648

Beck T, Demirgüç-Kunt A, Maksimovic V (2004a). “Financing Patterns around the World: Are Small Firms Different?” World Bank Mimeo.

Bönte N (2010), “Innovation, credit constraints and trade credit: evidence from a cross country study” Schumpeter discussion paper 2010-005

Braun M, Larrain B (2003). “Finance and the Business Cycle: International, Inter-Industry Evidence.” Cambridge, United States: Harvard University. Manuscript.

Brixiova Z, Kiyotaki N (1997). “Private Sector Development in Transition Economies. Carnegie-Rochester Conference Series on Public Policy vol.46.

Heckman JJ (1979). Sample Selection Bias as Specification Error. Econometrica, 47(1) :153 –161.

Laeven L (2003). “Does financial liberation reduce financing constraints?” Financ. Manage. 32(1):5-34.

Lung-Fei L (2001). "Self-selection". In Baltagi, B. A Companion to Theoretical Econometrics. Oxford: Blackwell. doi:10.1002/9780470996249

Maddala GS (1983). Limited Dependent and Qualitative variables in Economics, New York: Cambridge University Press, pp 257-291

Maddala GS (1986). “Limited-dependent and qualitative variables in econometrics. Cambridge”: Cambridge University Press.

Mina B, Zuzana BL (2011). Credit Constraints and Productive Entrepreneurship in Africa Political Economy Research Institute

National institute of statistics(NIS). 2009. Recensement général des entreprises 2009, principaux résultats

Puhani P (2000). "The Heckman Correction for sample selection and its critique". J. Econ, Surveys 14(1):53–68. doi:10.1111/1467-6419.00104

Slotty C (2009). Financial constraints and the decision to lease evidence from German SME. Working Paper Series: Finance & Accounting, No. 205.GoetheUniversität Frankfurt/M. July 2009.

Tieguhong JC, Mala WA, Ndoye O, Grouwels S, Useni KM, Betti JL (2012). Financial status of small and medium scale enterprises based on non-wood forest products (NWFP) in Central Africa, Forest Policy and Economics 20:112-119

World Bank/IFC (2002-2007). Enterprise Survey World Bank/ICF (2008), Doing Business: Measuring Business Regulations

World Development Indicators (WDI) 2007 Group. http://databank.worldbank.org/data/views/variableSelection/selectvariables.aspx?source=world-development-indicators


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