Journal of Economics and International Finance

Volume 8 Number 7 August 2016
ISSN 2006-9812

Academic Journals

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Journal of Economics and International Finance

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academicJournals

Vol. 8(7), pp. 93-105, August, 2016
DOI: 10.5897/JEIF2015.0684
Article Number: C98BF4059876
ISSN 2006-9812

http://www.academicjournals.org/JEIF

Journal of Economics and International Finance

Full Length Research Paper

Semi-Markovian credit risk modeling for consumer loans: Evidence from Kenya

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Received 6 June, 2015; Accepted 22 January, 2016

Based on simulations of implied values for credit worthiness over a period of 5 years for 1000 consumers, the study shows robustness of the Semi-Markovian models in forecasting Probabilities of Default and Loss Given Default for a portfolio of consumer loans. The study models credit risk as a reliability problem on the basis of which we generate credit risk indicators and quantify prospective capital holding based on forecast delinquencies. Consumer ratings are based on Monte-Carlo simulation techniques and the initial probability transition matrix on the Merton model. Banks could espouse the study results to fulfill regulatory credit risk capital requirements for consumer loans.

Key words: Semi-Markov models, credit risk, Central Bank of Kenya.

INTRODUCTION

This study seeks to respond to the need for better credit risk modeling for a portfolio of consumer loans in the Kenyan banking sector. To do this, the study briefly elucidates the credit risk models currently in use by Kenyan bankers and seeks to modify them through adapting the Semi-Markov approach to modeling credit risk. The study seeks to empirically establish a case for the adoption of the Semi-Markov credit risk framework in modeling through modeling credit rating migration patterns and establishing how the modeling of credit risk influences the solvency and capital adequacy of banks in Kenya in light of the Basel solvency requirements.

Credit risk management has been noted as the single most important role of a banks' management owing to their nature of business. Credit creation is the main income generating activity of banks, Kargi (2011). However, the downside to credit creation is the inherent credit risk that the bank is exposed to. Increasing variety in the types of counterparties and the expansion in the variety of the forms of obligations has necessitated the jump of credit risk management to the forefront of risk management activities carried out by firms in the financial service industry (Ali and Iraj, 2006). The financial crisis of 2008-2009 revealed that improper estimation of credit risk can lead to dramatic effects on the world's economy (Munnixl, 2011). A better estimation of credit risk is therefore important, a phenomenon addressed through credit risk modeling (Bluhm, 2002; Duffie, 2003; Giesecke, 2004; Lando, 2004; McNeil, 2005). Munnixl (2011) distinguished two fundamentally different approaches to modeling credit risk: the structural and the reduced form models.

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JEL: G21, G32

Structural models have a long history, going back to the work of Black and Scholes (1973) and Merton (1974). Reduced form models attempt to capture the dependence of default and recovery rates on macroeconomic risk.

The Kenyan banking sector has experienced a boom in the last few years marked with growth in net assets, branch network, regional expansion, growth in level of loans issued and an increase in the level of depositors, which is not typical to the pre-financial crisis banking sector in the developed economies such as the US.

CBK (2013) notes in its March, 2013 Credit Report Survey that credit risk is the single largest factor affecting the soundness of financial institutions and the financial system as a whole and lending is the principal business activity for most banks. A view re-echoed by Kargi (2011). CBK (2013) notes that the total percentage of loans to total assets for the period ended 31st March, 2013 was 57%, which prima facie, is good for business, however poses a potential threat to the industry if more loans became non-performing. Thus the need to effectively manage credit risk is inherent to the business of a bank. Credit risk modeling underpins this management.

With the newly issued risk guidelines, CBK (2013), the Central Bank of Kenya identifies internal rating models for banks as being key for effective credit risk management. This study's modeling of credit risk will therefore be a proxy of what a plausible portfolio of consumer loans' internal rating model, for credit risk management, could be. According to Jansen (2007), the credit risk problem can be seen as a reliability problem. In light of this, the rating process, carried out by a rating agency, gives a reliability degree of a firm bond. Moreover, the default state can be seen as a down state and an absorbing state. It is within this framework that Semi-Markov credit risk models become handy. Limnios (2000) specifies a critical application of Semi-Markov processes as being in reliability of mechanical systems. With the hypothesis that the next transition only depends on the immediate last one, this problem falls within the Markov processes framework. However, Limnios (2000) points out that, for a mechanical system, transition between two states usually happens after a random duration, not necessarily discrete time consequently, making the Semi-Markov environment a better fit than the Markov one. The study's results are of paramount importance to commercial banks, whose main business is credit creation, the regulator, CBK, as well as other corporate lenders, for instance corporate bond issuers.

LITERATURE REVIEW

The objective here is to articulate the conceptual foundations of the study. First is a survey of existing theoretical and empirical literature on the need for effective credit risk management. Next is a discussion of the current credit risk models in use within the Kenyan jurisdiction. Thereafter, an exploration of the need for better credit risk modeling techniques is presented, establishing a case for the Semi-Markov credit risk models.

The need for effective credit risk management

CBK (2013) annotates that credit risk is the current or prospective risk to earnings and capital arising from an Obligor's failure to meet the terms of any contract with a bank or if an obligor otherwise fails to perform as agreed. It further emphasizes that a bank's assets largely comprise loans making the management of credit risk extremely important. Njanike (2009) establishes that poor credit risk management was the chief reason that resulted in the demise of over ten banks in Zimbabwe during the 2003/2004 bank crisis in the southern African nation. The same can be said of the banking crisis in Kenya in the 1980s and in Spain in the 1990s.

While agreeing with Njanike (2009), Marrison (2002) articulates that the main activity of bank management is not mobilization of deposits and issuance of credit; however, risk management is paramount. He outlines that effective credit risk management reduces the risk of customer default. Moreover, they both add that the competitive advantage of a bank is dependent on its capability to handle credit valuably. Conducting a similar study in Spain, De Juan (2008) argues that banking failures were caused by poor credit risk management which was aggravated by the concentration of the loan portfolio in the group in which the bank itself belonged. Fredrick (2012), while using the CAMEL1 model as a proxy for credit risk established that credit risk management had an impact on the financial performance of commercial banks. He cites that the goal of credit risk management is to maximize a bank's risk adjusted rate of return through maintenance of credit risk exposure within acceptable limits. He articulates the need for credit risk management to be at the center of banks operations and cries foul at the lack thereof.

Current models and the case for semi-Markov models

CBK (2010) points to the application of the CAMEL rating system, an international benchmark, by the Central bank of Kenya in analyzing the soundness of financial institutions. Fredrick (2012) recognizes that numerous prior studies have examined the efficacy of the CAMEL ratings and they generally conclude that publicly available data combined with regulatory CAMEL ratings can identify and/or predict problem or failed banks. However, in a case study for the American International Assurance-

[1] **CAMEL:** refers to an acronym for Capital Adequacy, Asset Quality, Management, Liquidity and Sensitivity to Market Risk. The model identifies and measures the different aspects of a financial institution as stipulated in the acronym, aggregates them to obtain a single value which forms the basis of a rating, CBK (2012).

Vietnam, (AIA), it was established that the CAMEL model overlooks the provision as well as allowance for loan loss ratios. Heuristics modeling has also been identified as a key component of most Kenyan banks' credit risk models. However, Kithinji (2010) alludes to the fact that subjective decision-making by the management of banks may lead to extending credit to business enterprises they own or with which they are affiliated, to personal friends, to persons with a reputation for non-financial acumen or to meet a personal agenda, such as cultivating special relationship with celebrities or well-connected individuals.

Valle (2013) identifies three broad methodologies to model credit risk; structural form models (SFM), reduced form models (RFM) and factor models (FM). SFM are based upon the Black and Scholes theory for option pricing and the Merton model. Linda (2004), on the other hand, identifies two broad methodologies to modeling credit risk, an options-theoretic structural approach pioneered by Merton (1974) and a reduced form approach utilizing intensity-based models to estimate stochastic hazard rates. However, they both concur that the structural approach models the economic process of default, whereas reduced form models decompose risky debt prices in order to estimate the random intensity process underlying default. Consequently, RFM mainly focuses on the accuracy of the probability of default (PD), such that it is more important than an intuitive economical interpretation.

Under the Merton's structural model, default occurs after ample early warning (Linda, 2004). Consequently, default occurs after a gradual descent in the assigned behavioral value for consumers or asset values for firms; to the default point. This implies that the PD steadily approaches zero as the time to maturity nears (Valle, 2013). More realistic credit spreads are obtained from reduced form models (RFM) or intensity-based models (Linda, 2004). This holds since; whereas structural models view default as the outcome of a gradual process of deterioration in asset values/behavioral value, intensity-based models view default as a sudden, unexpected event, thereby generating PD estimates that are more consistent with empirical observations (Linda, 2004). This study uses a reduced form model for credit risk.

Valle (2013) notes that RFM can be classified as an individual level reduced form model (ILRFM) and portfolio reduced form model (PRFM).He further points out that the former is based on a credit scoring system (two-state or multistate), and the latter assumes an intensity jump process. The study takes the PRFM approach. PRFMs are reported to perform better in capturing the properties of credit risk (Cheng and Zhang, 2009). Within the PRFMs, Discrete Time Markov Processes (DTMP) and Continuous Time Markov Processes (CTMP) have been used in empirical studies to model credit risk spread as two components PD and LGD, (Vallay, 2013). The suitability of Markov processes in modeling credit risk has been challenged with notable problems being; the underestimation of migration probabilities by DTMPs, the dependence of the current state where the current state may depend on various previous states assigned to a firm or consumer and not only in the previous one, the waiting time in a state; among others (Linda, 2004). The Semi-Markov processes have been postulated as a solution to some of the DTMPs and CTMPs weaknesses (Duffie, 2003; D'Amico, 2005; D'Amico, 2009; Monteiro et al., 2006; Banachewicz and Lucas, 2007). This study models credit risk within the Semi-Markov framework.

The case for better credit risk modeling techniques

Chen and Pan (2012) indicate that the new Basel Capital Accord explicitly places the onus on banks to adopt sound internal credit risk management practices to assess their capital adequacy requirements. The Central Bank of Kenya (CBK) adopted the Risk Based Supervisory (RBS) approach in 2004 in cognizance of the limitations inherent in the traditional approach which prescribed a common supervisory approach to all institutions irrespective of differences in business activities conducted and risk appetites adopted (CBK, 2013). In managing credit risk, the CBK recommends that banks must receive sufficient information to enable a comprehensive assessment of the true risk profile of the borrower or counterparty. At a minimum, among the factors the bank should consider is the borrower's credit rating/report from a licensed credit reference bureau (CBK, 2013).

However, the ratings are bound to change, a factor that raises the credit risk to the bank, and which the CBK risk management guidelines don't provide for. The CBK guidelines, however note that an important tool in monitoring the quality of individual credits, as well as the total portfolio, is the use of an internal risk rating system which will allow more accurate determination of the overall characteristics of the credit portfolio, concentrations, problem credits, and the adequacy of loan loss reserves (CBK, 2013). However, no explicit mention of the working and parameterization or nature of such internal models is mentioned.

In its prudential guidelines, the CBK stipulates that capital requirements for a specific institution may increase or decrease depending upon its risk profile. An institution's minimum capital requirement (MCR) is calculated by dividing its Core and Total Capital by the sum of the value of its Risk-Weighted Assets for Credit risk, Market risk and Operational risk, to arrive at the minimum Tier One and Regulatory capital adequacy ratios respectively (CBK, 2013).

Under PG/03 (CBK, 2013), the Internal Capital Assessment Adequacy Planning (ICAAP) requires that institutions ensure that they at all times plan their capital ahead for a minimum of three years in order to establish and maintain on an ongoing basis an adequate level of capital, which would include an appropriate buffer, as determined by the board, above the regulatory required minimum capital. This requires institutions to have in place an appropriate and proportionate capital management strategy; hence the need to monitor exposure to different risks, especially credit risk. Of interest for this study is the lack thereof of robust models for forecasting capital requirements especially for credit risk purposes; given the nature of banks business; credit creation (Kargi, 2011). The CBK requires that an institution's Capital Adequacy Ratio must be at least 12%, of which 8% is Core Capital. In addition to the above minimum capital adequacy ratios of 8 and 12%, institutions are required to hold a capital conservation buffer of 2.5% over and above these minimum ratios to enable the institutions to withstand future periods of stress (CBK, 2013).

PG/04 (CBK, 2013) classifies loans, the major asset of banking institutions, into five categories: normal, watch, substandard, doubtful and loss. Classification is based on the number of days the loan is past its due repayment date. CBK (2013) portends that the CBK will conduct an on-site examination providing a list of reclassified accounts, some of which will be downgraded from categories earlier classified by the institution. No account from this list will be upgraded by the institution without sufficient justification.

Consequently, any classification should be in line with that of the regulator. Based on the classification, different amounts of provisioning are to be maintained. However, a prudent practice is to provide for more, in order to limit the downside risk of excessive exposure to non-performing loans. Incisive as this might be, could internal models aligned to the regulators requirements be able to capture exposure levels at different periods? Which would then inform capital adequacy and hence level of provisions made by a bank?

The strict regulation may explain the laxity in research in the area of credit risk modeling within the African jurisdiction. The non-multifariousness of most internal models due to the heavy reliance on regulatory provisions could explain the little or no use of intricate credit risk models.

However, even in light of regulation, the need to model credit risk, with its being the paramount risk that influences the capital levels of banks, is palpable. That less has been done is also ostensible.

A Semi-Markov framework will be adopted in modeling credit risk for a portfolio of consumer loans, as a proxy for an internal rating model for banks. For this study, initial rating of consumers is done through an initial score sheet that is backed by a logit model.

EMPIRICAL MODEL

This study seeks to empirically establish a case for the adoption of the Semi-Markov credit risk framework in through modeling credit rating migration patterns and establishing how the modeling of credit risk influences the solvency and capital adequacy of banks in Kenya in light of the Basel solvency requirements. Ross (2007) defines a Semi-Markov process by supposing that a process can be in any one of N states $1, 2, \ldots, N,$ and that each time it enters state i it remains there for a random amount of time having mean μ_i and then makes a transition into state j with probability p_{ij} Such a process is called a Semi-Markov process. With the view of the credit risk problem as a reliability problem, the process $Z = \{Z(t), t \geq 0\}$ is assumed to be a Semi-Markov process with kernel $\mathbb{Q}$. It describes the evolution of a consumer from one credit rating to another in time $t \geq 0$. The main reliability indicators are identified as:

The availability function defined as:

$$A_i\ (t) = \ P\left(Z\ (t)\epsilon U\ |Z(0) = \textstyle\sum_{j\epsilon U} \emptyset_{ij}(t)\ , i \in I\ i\right), i \in I \qquad (1)$$

$\emptyset_{ij}s$: The transition probability functions for the Z process.

The reliability function giving the probability that the system is always working in the time interval $[0, t]$:

$$R_i\ (t) = \ P\ (Z\ (t)\epsilon U\ |Z(0) = \ i), i \in U \qquad (2)$$

The maintainability function giving the probability that the system is down at time 0 and that the system will leave the set D within the time t,

$$M(t) = \ 1 - \ P(Z(u)\epsilon D, \forall u\ \epsilon(0, t]) \qquad (3)$$

Jacques and Raimondo (2007) delineate migration as the successive movement of credit ratings, which are estimates of the probability of default. They use the Standards and Poor's rating model to examine a firm's rating. This model has eight kinds of ratings (Radu, 2009), where the states are in decreasing order depending on the reliability of their debts and the default state D.

Jacques and Raimondo (2007) stipulate that in order to apply reliability models in a credit risk environment, based on the S&P classification, then the first seven states should be considered as 'good' states and the D state; the default state, the only 'bad' state and apply a Semi-Markov reliability model to the credit risk problem. State D is an absorbing state. They argue that in this case, only the $R(t)$ function is useful in this environment citing functions $A(t)$and $M(t)$ as meaningless. This argument was adopted in this study. $R_i\,(t)$ gives the probability that the system was always working up to the time t given that the system was in working state I at time 0.

D'Amico et al. (2009) state that in order to consider dependence of the rating evaluation from the lapse of time in which a firm remains in the same rating a homogeneous Semi-Markov process is introduced. Both Jacques and Raimondo (2007) and D'Amico et al. (2009) identify the following reliability indicators as key parts of the model.$\emptyset_{ij}(t)$ and $\emptyset_{ij}(s, t)$ which represent respectively the probabilities of being in the state j after a time t starting in the state i at time 0 in the homogeneous case and starting at time s in the state i in the non-homogeneous case. The Semi-Markov environment takes into account the different probabilities of state changes during the permanence of the system in the same state.

$R_i(t) = \sum_{j\epsilon U} \emptyset_{ij}(t)$ and $R_i(s,t) = \sum_{j\epsilon U} \emptyset_{ij}(s,t)$ which represents respectively the probabilities that the system never goes into default state in a time t in the homogeneous case and from time s to time t in the non-homogeneous case.

Both D'Amico et al. (2009), D'Amico (2010) and Jacques and Raimondo (2007) again agree on the following possible indicators useful that can be derived from the model.

$\varphi_{ij}(t) = P[Z(t) = j \mid Z(0) = i]$: The probability of a consumer being in the rank value j after a time t starting with the rank value i at time 0 which enables the accounting for the different transition probabilities during the permanence of the firm in the same rating.

$1 - H_i(t) = 1 - \sum_{j=1}^{m} Q_{ij}(t)$.

This is the stay on probability function representing the probability that in a time interval t there was no new rating evaluation for the consumer who started with rank i at the starting time. $\varphi_{iD} = \frac{p_{iD} - Q_{iD}(t)}{1 - H_i(t)}$ Which gives the probability that next transition of a consumer who entered the rank value i at time 0 and stayed on in the same rank till time t, will be in the default state.

$R_i(t) = P[Z(h) \epsilon U \; \forall h = 0,1,\ldots,t | Z(0) = i] = \sum_{j\epsilon U} \emptyset_{ij}^{r}(t)$: Which is the reliability function. It represents the probability that a consumer will never go into the default state in a time t. These indicators are adopted for the study.

The application of the formulated Semi-Markov migration model is dependent on data availed from existing ratings. Credit rating data is used to generate the initial transition matrix P. With inadequate rating data available, and the confidential nature of consumer loaners' information, the need to rate using a standard rating model for the different loaners, for homogeneity in rating in terms of variants, was apparent.

This study adopted a logistic regression model to establish the initial rating of a consumer, which was in line with the current practice at majority of Kenyan Banks. If x denotes the number of factors (their number being K) and b the weights attached to them, the score obtained on scoring instance i is:

$$Score_i = b_1 x_{i1} + b_2 x_{i2} \ldots + b_K x_{iK} = \boldsymbol{b}'\boldsymbol{x}_i \quad (4)$$

Where $\boldsymbol{b}$ and $\boldsymbol{x}$ are column vectors such that;

$$\boldsymbol{x}_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ . \\ x_{iK} \end{bmatrix} \text{ and } \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ . \\ b_K \end{bmatrix}$$

$$Prob\ Default_i = F(Score_i)$$

This study then defines F as the logistic distribution function $\Lambda(z)$ defined as

$$\Lambda(z) = {\exp(z)} \big/ {1 + \exp(z)}.$$

Applying this to the above result:

$$Prob\ Default_i = \Lambda(Score_i) = \frac{\exp(b'x_i)}{1+\exp(b'x_i)} = \frac{1}{1+\exp(-b'x_i)} \quad (5)$$

Andrade and Thomas (2005) suggest that using a consumer's behavioral score as a surrogate for credit worthiness of the borrower, one can adopt corporate structural models, the Merton model being most notable, to model for consumer credit risk. Consequently, consumers are assigned an initial behavioral value commensurate with the attained score. Subsequent rating is done using the Merton model for simulated values of the behavioral scores. The assumed period for the simulations is the preceding five years.

In the Merton model, (Merton, 1974), the value V of the firm is modeled with a Black and Scholes stochastic differential equation with trend u and instantaneous volatility (Jacques and Raimondo (2007).

$$V(t) = V_0 \, e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W(t)} \quad (6)$$

V_0 being the value of the firm at time 0 and $W = (W(t) | t\epsilon[0,T])$ a standard Brownian motion. If $V_i(t)$ corresponds to the behavioral score of consumer i at time t, as postulated by Andrade and Thomas (2004), $V_i(t)$ satisfies:

$$d\,V_i(t) - \mu_i + \sigma_i dW \quad (7)$$

μ_i is the drift of the process, corresponding to a natural drift in credit worthiness caused in part by the account and the customer ageing and so improving. $\sigma_i dW$ is a Brownian motion describing the natural variation in behavioral score. This study sought to rate consumers using the Merton model in light of the classification of loans (CBK, 2013). For this study;

$I = \{AAA, AA, A, BBB, BB, B, CCC, D\}$. Consequently $U = \{AAA, AA, A, BBB, BB, B, CCC\}$ and $D = \{D\}$.

The CBK provides the following loan classification based on the number of days the loan is past its due repayment date:

$N = \text{Normal}, W = \text{Watch}, SS = \text{Sub} - \text{Standard}, D = \text{Doubtful and } L = \text{Loss}$

To link the state space I with the current loan classification in the Kenyan Banking industry, the following events are identified: $N = \{AAA, AA, A\}$, $W = \{BBB, B\}$, $SS = \{B, CCC\}$, $D = L = \{D\}$

Where events N, W, SS, D and L are the Normal, Watch, Sub-Standard, Doubtful and Loss categories of loans as provided by the CBK through the CBK Prudential Guidelines

RESULTS AND DISCUSSION

Our empirical analysis establishes a case for the

Table 1. Initial transition matrix P for 1,000 consumers over five years.

P	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.93129	0.06044	0.00504	0.00148	0.00164	0.00009	0.00000	0.00001
AA	0.00464	0.94420	0.04326	0.00519	0.00100	0.00165	0.00002	0.00005
A	0.00051	0.01505	0.94403	0.02950	0.00697	0.00330	0.00004	0.00060
BBB	0.00030	0.00295	0.03704	0.90384	0.04110	0.00976	0.00105	0.00397
BB	0.00023	0.00148	0.00572	0.04727	0.85624	0.05887	0.00908	0.02111
B	0.00000	0.00096	0.00195	0.00351	0.03377	0.89002	0.02404	0.04575
CCC	0.00000	0.00004	0.00474	0.00535	0.01258	0.03479	0.85292	0.08958
D	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Table 2. Actual transition probabilities after three years $\emptyset_{ij}(3)$.

$\emptyset_{ij}(3)$	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.80851	0.15974	0.02087	0.00532	0.00441	0.00087	0.00006	0.00019
AA	0.01231	0.84446	0.11640	0.01706	0.00408	0.00491	0.00021	0.00059
A	0.00157	0.04065	0.84637	0.07682	0.02064	0.01039	0.00059	0.00297
BBB	0.00088	0.00938	0.09609	0.74676	0.09736	0.03050	0.00410	0.01496
BB	0.00062	0.00444	0.01931	0.11127	0.63849	0.13706	0.02376	0.06505
B	0.00004	0.00269	0.00630	0.01326	0.07863	0.71263	0.05566	0.13079
CCC	0.00002	0.00049	0.01245	0.01473	0.03135	0.08151	0.62299	0.23646
D	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Table 3. Actual transition probabilities after seven years $\emptyset_{ij}(5)$.

$\emptyset_{ij}(5)$	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.61190	0.29068	0.06603	0.01617	0.00926	0.00404	0.00043	0.00144
AA	0.02260	0.68420	0.22039	0.04332	0.01303	0.01172	0.00110	0.00370
A	0.00371	0.07754	0.69613	0.13727	0.04458	0.02537	0.00297	0.01245
BBB	0.00195	0.02281	0.17073	0.53262	0.14630	0.06744	0.01157	0.04663
BB	0.00122	0.01037	0.04801	0.16517	0.38227	0.19812	0.04113	0.15372
B	0.00022	0.00564	0.01617	0.03447	0.11364	0.47548	0.07867	0.27572
CCC	0.00012	0.00221	0.02311	0.02862	0.05080	0.11805	0.33879	0.43830
D	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

adoption of the Semi-Markovian modeling of credit risk for a portfolio level consumer loans, as a plausible internal credit rating model for the Kenyan banking industry. Table 1 presents the generated initial transition matrix based on the simulations on 1,000 consumers over five years.

Tables 2 and 3 represent the transition probabilities obtained by solving the evolution equation for some times, in the homogeneous case. The transition probabilities were generated from the initial transition matrix P, at different times for $(0 \leq t \leq 12)$. Each $\emptyset_{ij}(t)$ represents the probability of a consumer being in the rank value j after a time t starting with the rank value i at time 0.

For the homogeneous case, the following transition probabilities were generated from the initial transition matrix P and subsequent transition matrices that is, $P^n; 1 \leq n \leq 12$, for each $\emptyset_{ij}(t)$ at different times t; $(1 \leq t \leq 12)$, as presented in Tables 4 and 5. Each $\varphi_{ij}(t)$ the probability of a consumer being in the rank value j after a time t starting with the rank value i at time 1 which enables the accounting for the different transition probabilities during the permanence of the firm

Table 4. Projected transition probabilities after three years $\varphi_{ij}(3)$.

$\varphi_{ij}(3)$	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.65325	0.12907	0.01686	0.00430	0.00357	0.00070	0.00005	0.00015
AA	0.01038	0.71160	0.09809	0.01438	0.00343	0.00414	0.00018	0.00050
A	0.00133	0.03427	0.71350	0.06476	0.01740	0.00876	0.00050	0.00250
BBB	0.00065	0.00695	0.07122	0.55347	0.07216	0.02261	0.00304	0.01109
BB	0.00039	0.00281	0.01219	0.07024	0.40304	0.08652	0.01500	0.04106
B	0.00003	0.00190	0.00446	0.00938	0.05564	0.50423	0.03939	0.09254
CCC	0.00001	0.00030	0.00774	0.00915	0.01948	0.05064	0.38706	0.14691
D	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Table 5. Projected transition probabilities after five years $\varphi_{ij}(5)$.

$\varphi_{ij}(5)$	AAA	AA	A	BBB	BB	B	CCC	D
AAA	0.70287	0.23492	0.04195	0.01027	0.00686	0.00224	0.00020	0.00064
AA	0.01818	0.75850	0.17451	0.03004	0.00821	0.00825	0.00058	0.00178
A	0.00265	0.06117	0.76474	0.11176	0.03330	0.01785	0.00162	0.00692
BBB	0.00143	0.01611	0.13934	0.62617	0.12951	0.05027	0.00779	0.02942
BB	0.00094	0.00742	0.03388	0.14710	0.48780	0.17895	0.03421	0.10969
B	0.00012	0.00423	0.01111	0.02416	0.10266	0.57843	0.07200	0.20731
CCC	0.00006	0.00126	0.01841	0.02244	0.04349	0.10671	0.45781	0.34982
D	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	1.00000

Table 6. The credit indicators $R_i(t)$, giving the probability that the 'system' was always working up to the time t given that the system was in working state I at time 0.

$R_i(t)$	AAA	AA	A	BBB	BB	B	CCC	D
1	0.99999	0.99995	0.99940	0.99603	0.97889	0.95425	0.91042	0.00000
2	0.99993	0.99976	0.99841	0.99101	0.95712	0.91065	0.83213	0.00000
3	0.99981	0.99941	0.99703	0.98504	0.93495	0.86921	0.76354	0.00000
4	0.99962	0.99890	0.99525	0.97819	0.91262	0.82990	0.70328	0.00000
5	0.99936	0.99822	0.99308	0.97058	0.89031	0.79269	0.65018	0.00000
6	0.99901	0.99735	0.99051	0.96228	0.86815	0.75751	0.60327	0.00000
7	0.99856	0.99630	0.98755	0.95337	0.84628	0.72428	0.56170	0.00000
8	0.99802	0.99505	0.98422	0.94394	0.82477	0.69294	0.52475	0.00000
9	0.99737	0.99361	0.98052	0.93407	0.80371	0.66338	0.49181	0.00000
10	0.99661	0.99195	0.97647	0.92381	0.78315	0.63553	0.46235	0.00000
11	0.99572	0.99009	0.97208	0.91324	0.76313	0.60930	0.43592	0.00000
12	0.99472	0.98803	0.96737	0.90240	0.74367	0.58459	0.41213	0.00000

in the same rating. The credit indicators $R_i(t)$, giving the probability that the 'system' was always working up to the time t given that the system was in working state I at time 0 and the stay on probability function, $1 - H_i(t) = 1 - \sum_{j=1}^{m} Q_{ij}(t)$; representing the probability that in a time interval t there was no new rating evaluation for the consumer starting with rank i at the starting time are presented in Table 6 and 7 respectively.

Discrete Time Markov Processes (DTMP) and Continuous Time Markov Processes (CTMP) have been used in empirical studies to model credit risk spread as two components; PD and LGD, Valle (2013). Consequently, the study focused on the PD and LGD components of the Basel formula for computing regulatory credit risk capital. The credit risk capital Basel formula is

Table 7. Stay on probability function, $1 - H_i(t) = 1 - \sum_{j=1}^{m} Q_{ij}(t)$; representing the probability that in a time interval t there was no new rating evaluation for the consumer starting with rank i at the starting time.

$1 - H_i(t)$	AAA	AA	A	BBB	BB	B	CCC	D
1	0.93129	0.94420	0.94403	0.90384	0.85624	0.89002	0.85292	1.00000
2	0.80797	0.84266	0.84301	0.74116	0.63125	0.70757	0.62129	1.00000
3	0.65325	0.71160	0.71350	0.55347	0.40304	0.50423	0.38706	1.00000
4	0.49236	0.56921	0.57348	0.37778	0.22423	0.32320	0.20654	1.00000
5	0.34607	0.43174	0.43856	0.23656	0.10938	0.18695	0.09456	1.00000
6	0.22691	0.31086	0.31969	0.13637	0.04708	0.09789	0.03721	1.00000
7	0.13885	0.21269	0.22255	0.07264	0.01800	0.04655	0.01260	1.00000
8	0.07932	0.13843	0.14820	0.03587	0.00615	0.02016	0.00368	1.00000
9	0.04232	0.08580	0.09458	0.01647	0.00189	0.00797	0.00093	1.00000
10	0.02109	0.05069	0.05793	0.00706	0.00053	0.00289	0.00020	1.00000
11	0.00983	0.02858	0.03412	0.00283	0.00013	0.00096	0.00004	1.00000
12	0.00428	0.01539	0.01934	0.00107	0.00003	0.00029	0.00001	1.00000

provided as part of the Appendix I. The formula calibrates for suitable standardized values of MF, ρ_i and an α for computing EAD.

From the Semi-Markov model adopted, the computed $\emptyset_{ij}(t)'s\ \ for\ (0 \leq t \leq 12)$, are analogous to $PD_i's$ in the formula. However, it is the ability of the Semi-Markov model to predict the probabilities of default over longer durations that makes it appealing for forecasting. This is in sync with the Internal Capital Assessment Adequacy Planning (ICAAP) requirement for institutions to ensure that they at all times plan their capital ahead for a minimum of three years, CBK (2013). Each $\emptyset_{ij}(t)$ represents the probability of a consumer being in the rank value j after a time t starting with the rank value i at time 0. The study results generate default probabilities for periods greater than three years. Consequently, determining the level of capital reserves to be held due to credit risk is facilitated. Meanwhile, aside from holding capital due to default, the study results facilitate the holding of capital for other loan classifications by providing probabilities of consumer loans being in the other states that would trigger provision. Provisioning is also done prior to occurrence of loss event, further protecting the firm against delinquent events.

The study illustrates the applicability of the model through Customer A, B and C who were randomly selected, ; appraised as per the metrics in the credit evaluation sheet; assigned initial probabilities of default based on their initial scores and assigned initial implied values V_o. Appendix I provides a summary of their details Appendix II provides summary of the reserve required for a portfolio of the three customers A, B and C in three years' time, denoted Reserve_1. Of interest to a bank apart from the probability of default after a given period of time, is the probability that in a time interval t there is no new rating evaluation for a consumer starting with rank i at the starting time. This is represented as the probability $1 - H_i(t)$, presented in Table 7. It is the stay on probability. Consequently, it is possible for a bank to compute the capital reserves for a portfolio of consumer loans after say 3 years, assuming the stay on probabilities over the three years. This provides the expected reserve if the consumers credit worthiness doesn't deteriorate nor improve over a given interval of time.

Appendix II provides capital reserves computed after an interval of three years, given the stay-on probabilities for the sample consumers, A, B and C, denoted $Reserve_2$. Moreover, a bank would be concerned with the permanence of a consumer in a state, their subsequent movement to a different state and the effect of this on the amount of capital reserves required.

This is represented by each, the probability of a consumer being in the rank value j after a time t starting with the rank value i at time 1 which enables the accounting for the different transition probabilities during the permanence of the firm in the same rating. Appendix II provides the capital reserve requirement at time 3 for the portfolio of sample consumers, denoted Reserve_3. Finally, a bank's credit risk function is at all times concerned about the soundness of its portfolio of consumer loans given the assumed probabilities of default.

To establish the extent of exposure at any time in future, the Semi-Markov credit risk indicator provides the probability that the consumer has no default in a time t starting in the state i at time 0. As evident from the values provided in Table 4, there is less than 10% chance that any consumer loan will default in the first year. In fact, the highest probability of default is for a consumer initially rated CCC, with probability 0.08958.

The probabilities of having no default deteriorates with time as expected. However, up until time three, the probability of default for a consumer in any rating is still below 40%, an indication that there is less than 40% chance of the portfolio of consumer loans becoming non-performing in the next three years. Further inferences over different durations can be made similarly.

A comparison of the adequacy of reserves provided through the Semi-Markov approach and the current Kenyan banking industry practice was apparent however not feasible. Apart from the lack of data upon which to base such analysis, there was also the need for a common time frame. Majority of Kenyan banks' forecasts for credit risk is over a period of 1 year. Meanwhile, classification of loans into the separate classes i.e. Normal, Watch, Sub-Standard, Doubtful and Loss, is a retrospective process that follows after a consumer fails to make good their loan repayments. To the contrary, the Semi-Markov model is a prospective model.

Though the results of the Semi-Markov credit risk model may be reliable, the fact that the data values were simulated may not be representative enough of the Kenyan banking industry. Nevertheless, the fact that this model is better in forecasting credit risk indicators for a portfolio of consumer loans is evident, which attains the objective of the study: Establishing a case for the adoption of the Semi-Markov credit risk framework in modeling of credit risk for a portfolio of consumer loans through modeling credit rating migration patterns and how this influences the solvency and capital adequacy of banks in Kenya in light of the Basel solvency requirements.

Conclusion

With considerable progress having been made in the area of modeling consumer credit risk, the use of RFMs to model credit spreads has been acclaimed as more realistic to other models. RFMs view default as a sudden, unexpected event, thereby generating PD estimates that are more consistent with empirical observations (Linda, 2004). Consequently, they are preferable. The Basel Accord recommends that banks have an internal rating model for their credit risk exposures. Meanwhile, the CBK Risk Guidelines note that an important tool in monitoring the quality of individual credits, as well as that of the portfolio, is the use of an internal risk rating system which will allow more accurate determination of the overall characteristics of the credit portfolio, concentrations, problem credits, and the adequacy of loan loss reserves (CBK, 2013).

The study concludes that indeed there is a need to model credit risk for effective credit risk management by banks. The inadequacy of the current risk management practice among Kenyan banks is apparent. Non-multifarious and highly subjective credit risk models have consistently been used and their inability to adequately capture credit risk and forecast the probability of default over longer durations has been established. It is concluded that this is a distressing trend since it implies inadequacy of capital reserves held by banks for credit risk. Under CBK (2013), the Internal Capital Assessment Adequacy Planning (ICAAP) requires that banks ensure that they at all times plan their capital ahead for a minimum of three years in order to establish and maintain on an ongoing basis an adequate level of capital, which would include an appropriate buffer, as determined by the board, above the regulatory required minimum capital.

The study further concludes that there is need for robust internal credit risk models. To respond to the need, the study adopted a PRFM, the Semi-Markov model, given the ability of PRFMs to model credit risk spread as two components PD and LGD (Valle, 2013). The study sought to pitch for the case of the Semi-Markov credit risk models in light of the aforementioned regulatory requirements and the need for more robust credit risk models.

Initial credit scoring of randomly selected consumers was done in line with the current practice in the Kenyan banking sector. To each initial credit score, an implied value which acts as the proxy for credit worthiness of the specific consumer; was then assigned. Subsequent rating was done through the Merton model through which the initial transition matrix was generated assuming past historical values for credit worthiness for a portfolio of consumer loans. The initial transition matrix was then espoused to the Semi-Markov environment. The study concludes; from the analysis, results and discussion; the Semi-Markov models not only respond to the existent need for better credit risk modeling but go as far as forecasting for periods beyond the required regulatory minimum of three years.

Whether the capital reserves computed from the Semi-Markov framework are more sufficient than the existent capital reserves for portfolios of consumer, loans computed through standard industry practice could not be verified in the study. This was due to the reluctance by banks to provide such information. Nonetheless, from the study results and discussion, the Semi-Markov framework facilitates better prediction of default probability, the extent of exposure and hence facilitates adequate capital provision prior to occurrence of loss event i.e. default. Lack of data to facilitate the modeling process, was the only challenge to the generation of results and the proceeding analysis. The use of *Monte-Carlo* simulated data however facilitated passable deductions.

Conflict of Interests

The authors have not declared any conflict of interests.

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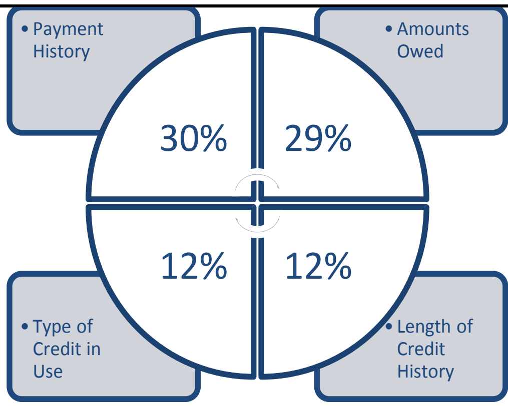
Appendix I. Consumer A, B and C.



Inferences

Overall % =83%

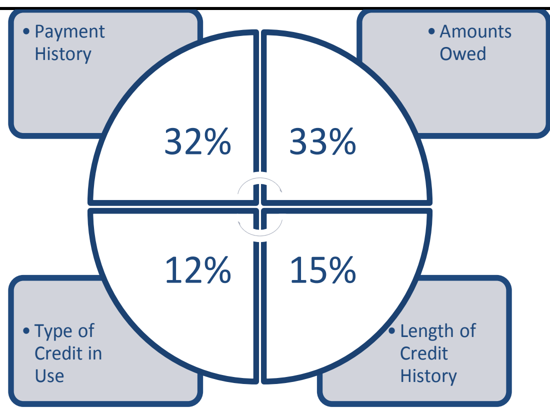
Implied Vo=Overall%*200=166

Initial Scoring=(3)

Initial Rating=BBB

Initial Probability of Default=4.74%

Consumer A



Inferences

Overall % =91%

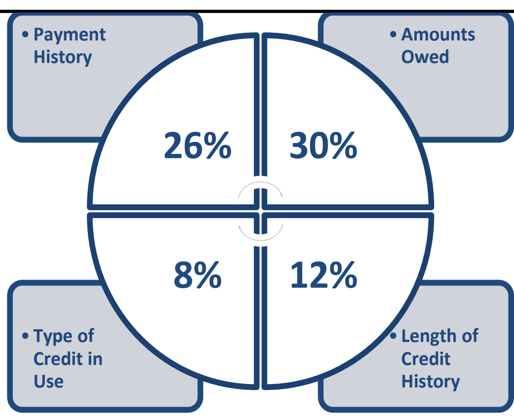
Implied Vo= Overall%* 200=184

Initial Scoring=(7)

Initial Rating=AA

Initial Probability of Default=0.09%

Consumer B



Inferences

Overall % =76%

Implied Vo= Overall%* 200=152

Initial Scoring=(2)

Initial Rating=BB

Initial Probability of Default=11.92%

Consumer C

Appendix II. Reserves.

Reserve	Amount (KES)
$Reserve_1$.	283,143
$Reserve_2$.	144,532
$Reserve_3$.	186,378

Appendix III. Basel credit risk capital formula.

The Basel II regulatory capital formula for credit risk is as stipulated below:

$$Credit\ Risk_{reg\_Cap} = \sum_{i=1}^{N} LGD_i * EAD_i * \left[\Phi\left(\frac{\Phi^{-1}(PD_i) - \sqrt{\rho_i}\,\Phi^{-1}(0.001)}{\sqrt{1-\rho_i}}\right) - PD_i\right] * MF(M_i, PD_i)$$

Where:

$Credit\ Risk_{reg\_Cap}$ = the Internal Risk Based Credit risk regulatory capital
LGD_i = Loss given default for consumer i; proportion of exposure lost if default occurs
EAD_i = Exposure at default for consumer i
PD_i = Probability of default of consumer over a period of 1 year
ρ_i = Correlation of 'assets'. For the study, this is the correlation of the consumer behavioral values
MF = Maturity Factor. It captures the incremental credit risk capital due to credit **migration**

Appendix IV. Score sheet.

Payment History [35%] Other Accounts			
Account type	**Assign 1 or 0**	**Initial Amount Owing (KES)**	**Repayment Amount Monthly (y_i) (KES)**
Credit Account			
Retail Account			
Installment Loan			
Finance Company Account			
Mortgage Account			
Total	$x/6$		$q = \{y/_{Monthly\ Income}\}$

Other Accounts	**Payment history**
Value of q	Initial Amount Owing (KES)
> 0.3	75%
$= 0.3$	50%
< 0.3	25%
Total	

$$\text{Total} = \left\{\frac{x}{6} * (1+q)\right\}$$

Payment history [35%] Public Record and Collection Items		
Event	Assign 0 or 1	$z/5$
Date of event	Assign t%	
$0 - 360$	100%	
$361 - 720$	75%	
$721 - 1080$	50%	
> 1080	25%	
$Total = \frac{z}{5} * ((1+t_1) + \cdots (1+t_z))$		

Delinquencies

How late (Days):	☐ *0-30*	☐ *31-60*	☐ *61-90*	☐ *>90*
Assign (d %)	*25%*	*50%*	*75%*	*100%*

How much was owed: o

Initial Loan Amount: P

Delinquency Date:	$0-360$	$361-720$	$721-1080$	>1080
Assign (t %)	*100%*	*75%*	*50%*	*25%*

Number of Delinquency Cases in the last 1 year: Assign 0 or 1 (A total of n cases)

$$Total = \frac{1}{n}\left\{\langle(1+d_1) * {}^{o_1}/_{p_1} * (1+t_1)\rangle + \cdots + \langle(1+d_n) * {}^{o_n}/_{p_n} * (1+t_n)\rangle\right\}$$

$$\textit{Payment History}\ \text{Overall}\ \textit{Total} = \left[\left\{\frac{x}{6} * \langle 1+q\rangle\right\} + \frac{1}{n}\left\{\langle(1+d_1) * {}^{o_1}/_{p_1} * (1+t_1)\rangle + \cdots + \langle(1+d_n) * {}^{o_n}/_{p_n} * (1+t_n)\rangle\right\} - \frac{z}{5} * \langle(1+t_1) + \cdots (1+t_z)\rangle\right] * 35\%$$

Account Type	Amounts Owed		
	N^o of Payments Made f_i	Initial Amount Owing (P_i) (KES)	Proportion Outstanding During New loan Term (K_i)
Credit Account			
Retail Account			
Installment Loan			
Finance Co Account			
Mortgage Account			
Total			

$$Where\ K = \frac{Initial\ Amount\ Owing - N^o\ of\ Payments\ made * Repayment\ Amount}{Initial\ Amount\ Owing}$$

$$K_i = \frac{P_i - f_i * Repayment\ Amount}{P_i}$$

$$Amounts\ \textit{Owed Total} = \left[\frac{1}{\textit{Total Accounts Outstanding}} * \langle 1 - \sum_{\forall i} K_i\rangle\right] * 35\%$$

Length of Credit History [15%] and Types of Credit in Use [15%] sections will be scored from these two prior sections.

academicJournals

Vol. 8(7), pp. 106-126, August, 2016
DOI: 10.5897/JEIF2016.0743
Article Number: C1AE2FD59878
ISSN 2006-9812

http://www.academicjournals.org/JEIF

Journal of Economics and International Finance

Full Length Research Paper

Macroeconomic variables and stock market performance of emerging countries

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Received 6 January, 2016; Accepted 18 May, 2016

This article seeks to fill the gap of severe data limitations on the link between macroeconomic variables and stock market performance. A panel data of 41 emerging countries for the period 1996 to 2011 was used to estimate the results. The model used by Sangmi and Mubasher (2013) was adopted and modified to determine the effect of macroeconomic variables on stock market capitalization. The four techniques to investigate the effects were robust ordinary least squares (OLS), FGLS, dynamic ordinary least squares (DOLS) and then Newey-West. It was discovered that depreciation in exchange rate in dollars and reduction in consumer price index affects stock market development negatively, while increase in money supply does influence stock market positively. The findings highlight the significance of macroeconomic factors such as consumer price index, exchange rate, money supply and GDP in explaining the stock market performance in emerging stock economies.

Key words: Stock Market Capitalization, Money Supply, Consumer Price Index, GDP and Stock Market

INTRODUCTION

The stock market plays a vital role in the modern economy since it acts as a mediator between lenders and borrowers. Financial markets, especially stock markets, have contributed considerably to the development of emerging economies over the last two decades. This trend is recorded at the same time that these economies are characterized with stable macroeconomic variables. The market capitalization of emerging stock markets rose from $604 billion to $3,074 billion for the period of 1990 to 1999. The trend continued in 2000 with countries like Malaysia, Jordan, Jamaica, Chile, Saudi Arabia, Thailand, and Philippines accounting for the rise in stock market capitalization. This trend is supported by Figure 1. It could be deduced that after 2000 most markets saw an increase in Stock Market Capitalization (SMC) as shown by markets sampled in this article.

Interestingly, countries cited as having high stock market capitalization over the period under study recorded low average GDP. The trend shows an inverse relationship between GDP and stock market capitalization which do not conform to literature reviewed in this article and hence raises questions worth researching. Various macroeconomic variables affect stock market behavior in line with intuitive financial theory (Maysami and Koh, 2000) for which existing literature provides number of theories illustrating the link between stock market behavior and macroeconomic variables. The effect of macroeconomic variables on the stock

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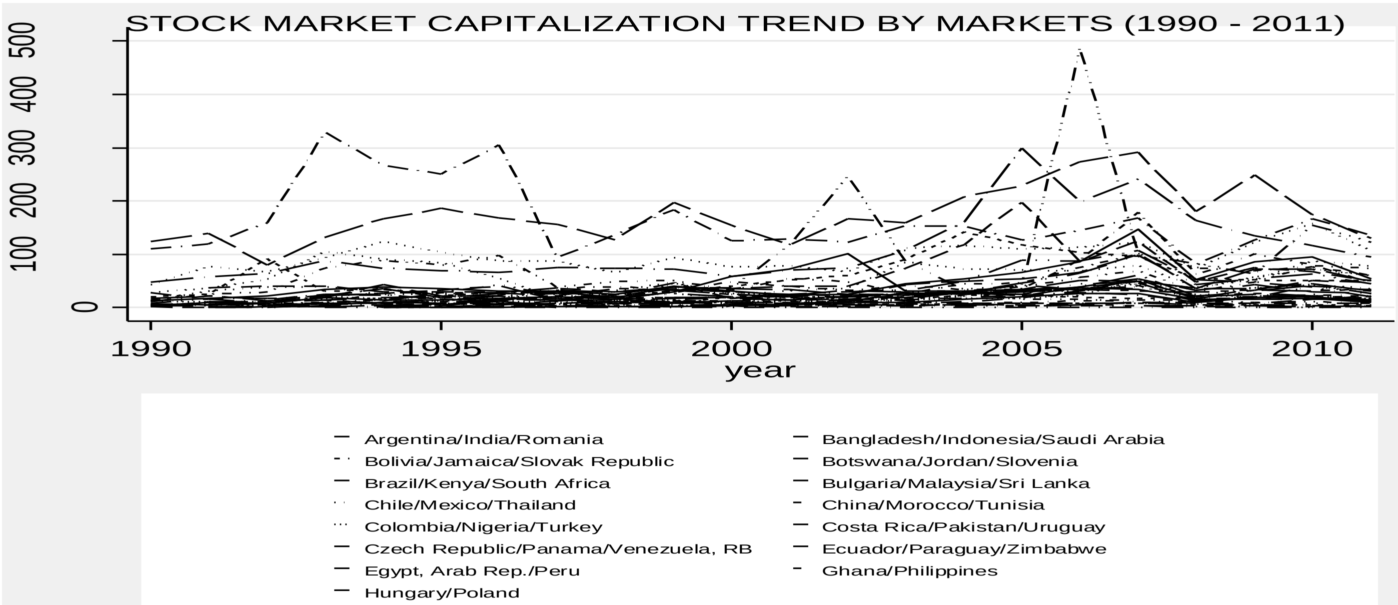

Figure 1. Stock market capitalization trend by markets (1990 to 2011).

market characteristics is deep-rooted in literature. However, more studies are focused on the developed countries such as the US, UK and Japan (Fama, 1981; Hamao, 1988; Chen, 1991; Poon and Taylor, 1992) than we have for emerging economies.

The work of Garcia and Liu (1999) established that macroeconomic volatility does not affect stock market performance, while Maku and Atanda (2010) established that stock market performance in Nigeria is mainly affected by macro-economic factors in the long run. Ting et al. (2012) established that Kuala Lumpur Composite Index is consistently influenced by interest rate, money supply and consumer price index in the short run and long-run in Malaysia. Mehwish (2013) recognized a negative relationship between real interest rate and stock market performance in Pakistan. Consumer price index and interest rate have significant impact on the stock market performance in Bangladesh according to the findings of Jahur et al. (2014).

A regression analysis conducted by Aduda et al. (2012) reported that there is no relationship between stock market development and Macro-economic stability - inflation and private capital flows. Mongeri (2011) established that foreign exchange rates have a negative significant impact on stock market performance. Also, Songole (2012) established that market interest rate, consumer price index and exchange rate have a negative relationship with stock return. Ochieng and Adhiambo (2012) established that 91 – day T-bill rate has a negative relationship with the NASI while inflation has a weak positive relationship with the NASI. Kimani and Mutuku (2013) showed that there is a negative relationship between inflation and stock market performance.

There has being no research in an attempt to explain the current performance of stock markets in emerging economies in relation to macroeconomic variables that have seen remarkable improvement for emerging economies over sampling period of this article 1996 to 2011. We argue that macroeconomic instability and ceteris paribus negatively impacts stock market development.

In contrast to this study, many researchers such as Black et al. (1997), Hamao and Campbell (1992), Chen et al. (1986), Cochran et al. (1993), Fama and French (1989), Harvey et al. (2002) and Schwert (1990) have based their analysis on business cycle variables or stock market valuation measures such as the term spread or dividend yield. These variables are usually found to be stationary which is the reason why they were not accounted for.

The main objective of this article is to examine the effect of the selected macro-economic (consumer price index, money supply, and exchange rate in dollars) and GDP on stock market performance in emerging economies.

Hypotheses

i. H_0: There is no significant relationship between the designed macroeconomic variables and stock market performance of emerging countries. This hypothesis tests the relationship between consumer price index, money supply, and exchange rate in US dollars.
H_1: There is significant relationship between the designed macroeconomic variables and stock market performance

of emerging countries. This hypothesis tests the relationship between consumer price index (-), money supply (+) and exchange rate in dollars (-).

Descriptive statistics of emerging stock market sampled

To understand the economic importance of the stock market in the sample of 41 countries, the stock market capitalization ratio was examined. The choice of countries and times series data for this article rests on the availability of data. Data for this article are from Worldwide Governance indicators, World Development Indicator (WDI) and Global Finance and Development (GFD). The stock market capitalization ratio is defined as the value of domestic equities traded on the stock market relative to GDP. As can be observed from Appendix 1, stock market development indicators exhibit a considerable variability across countries, according to the stock market capitalization ratio. The top ten countries in terms of mean stock market capitalization for the period under review are South Africa, Malaysia, Jamaica, Jordan, Chile, Zimbabwe, Saudi Arabia, Thailand, Philippines and India in that order. The countries with lowest stock market capitalization are Ecuador, Slovak Republic, Bangladesh, Paraguay and least Uruguay. As can be seen in stock market development in terms of total value trade as percentage of GDP, South Africa moved from the first to third position with Saudi Arabia occupying the first position from our sample. Stock market capitalization has very little to do with the size of a country. China, which has the largest economy by far among these countries, has a smaller average market capitalization than Hong Kong over the period. South Africa and Taiwan approached China in terms of stock market capitalization despite vastly smaller population and GDP. Again even though Nigeria has a larger economy than Ghana, Ghana is ahead of Nigeria in terms of stock market capitalization as a measure of development of the capital market.

A National Bureau of Economic Research (NBER) Working Paper in April, 2013 on Financial Development in 205 Economies, 1960 to 2010, has gathered substantial evidence that financial institutions (such as banks and insurance companies) and financial markets (including stock markets, bond markets, and derivative markets) exert a powerful influence on stock market development, poverty alleviation, and economic stability. Stock market development has been central to the domestic financial liberalization programs of most emerging markets. Apart from their role in domestic financial liberalization, the stock markets have also been very important in recent years as a major channel for foreign capital flows to emerging economies. Net equity flows to the emerging markets have grown over the years, providing an important source of capital for development. The share of foreign direct investment and portfolio equity in the finance mix of many developing countries has grown in recent years. Equity flows accounted for 80% of total external financing to developing nations during 1999 to 2003, compared with just 60% during 1993 to 98 (Global Development Finance, 2005). Cross-border capital flows, which include lending, foreign direct investment and purchases of equity and bonds, rose to a peak of $11.8 trillion in 2007, primarily due to the acceleration in interbank lending with a smaller share being the flow of funds to real economy borrowers. According to a McKinsey Global Institute (MGI) study, as of 2012, cross-border capital flows had declined by 61% from the 2007 peak to $4.6 trillion. Most of this reduction was in intra-European flows, thus raising the share of global capital flows to emerging economies to 32% in 2012 ($1.5 trillion) from 5% in 2000. Capital flows out of developing countries rose to $1.8 trillion in 2012.

Development of stock markets in emerging market does not imply that even the most advanced emerging stock markets are mature. Trading occurs in only a few stocks which account for a considerable part of the total market capitalization. Beyond these actively traded shares, there are serious informational and disclosure deficiencies for other stocks. There are serious weaknesses in the transparency of transactions on these markets. The less developed of the stock markets suffer from a far wider range of such deficits. Compared with the highly organized and properly regulated stock market activity in the US and the UK, most emerging markets do not have such a well-functioning market. Not only are there inadequate government regulation, private information gathering and dissemination firms as found in more developed stock markets are inadequate. Moreover, young firms in emerging stock markets do not have a long enough track record to form a reputation. As a result, one expects share prices in emerging markets to be arbitrary and volatile (Tirole, 1991). Empirical evidence indicates that share prices in emerging markets are considerably more volatile than in advanced markets.

Despite this volatility, large corporations have made considerable use of the stock market. For example, the Indian stock market has more than 8,000 listed firms, one of the highest in the World. Looking at the corporate financing pattern in emerging markets it was found that contrary to expectation, emerging market corporations rely heavily on external finance and new equity issues to finance long term investment and the stock markets have been successful in providing considerable funds.

Market liquidity is one the measures of stock market development. Market Liquidity is ability for investors to buy and sell shares. Stock market performance was measured using total value traded as a share of GDP, which gives the value of stock transactions relative to the size of the economy. According to the work of Levine and Zervos (1998) this measure is used to gauge market liquidity. This is because it measures trading relative to

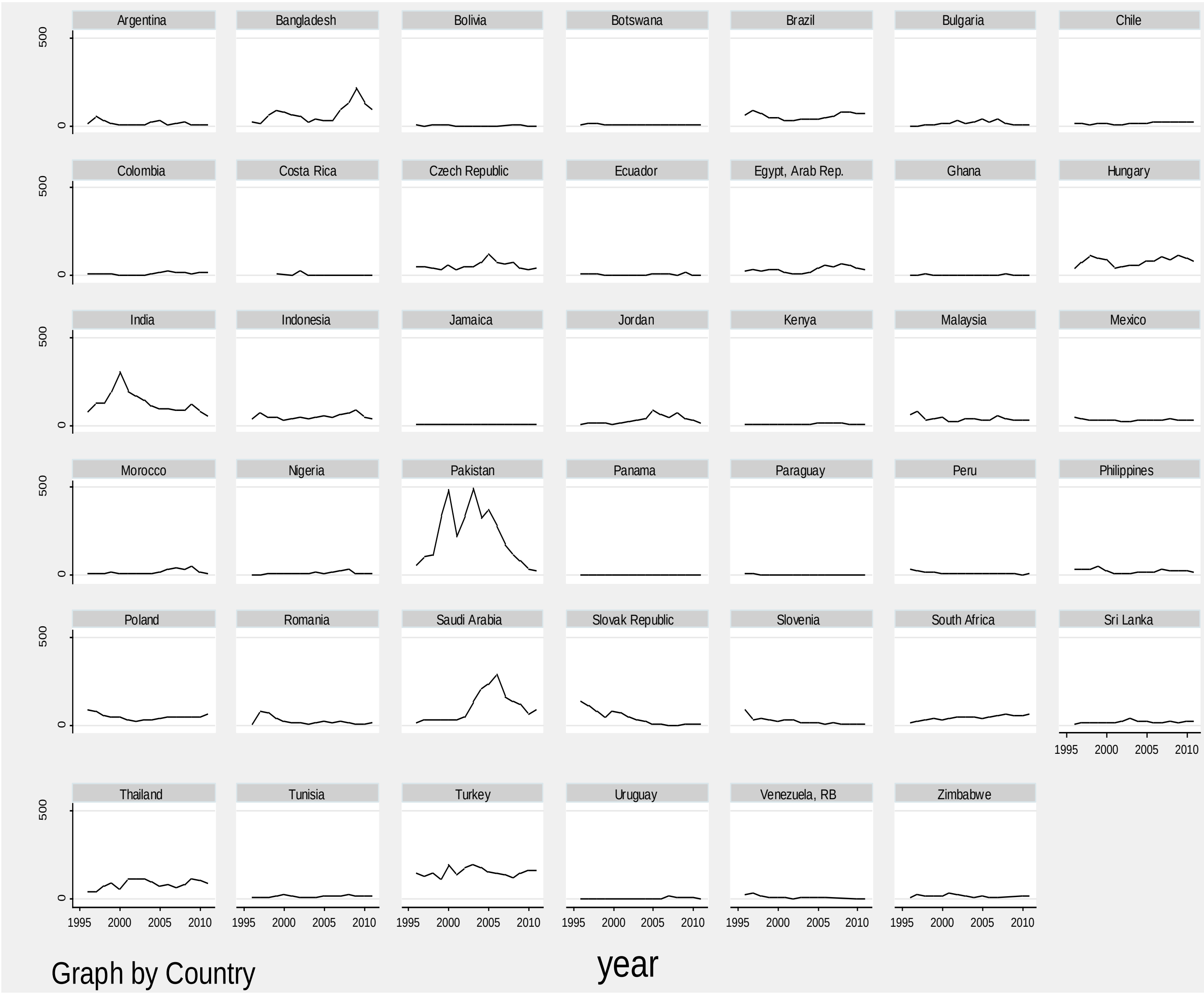

Figure 2. Annual percentage changes of turnover (1996 to 2011). Source: WDI

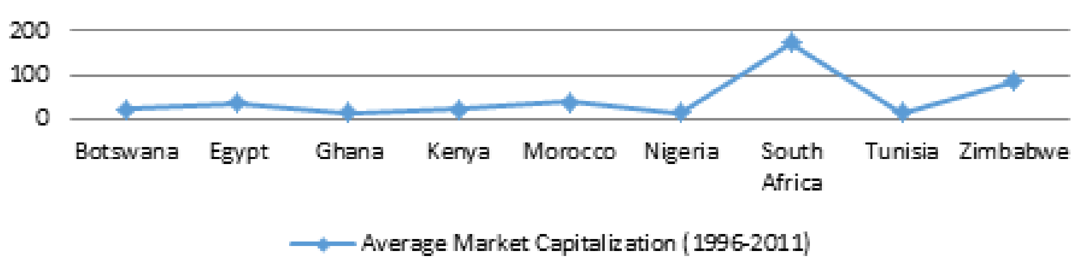

Figure 3. Emerging economies in Africa.

economic activity. Of the 41 countries Pakistan, Saudi Arabia, Bangladesh, Turkey and India turned out to be countries with liquidity as shown in Figure 2. The liquidity in these countries was recorded around the late 90's and the early part of 2000 was the time most of these countries have undertaken successful financial liberalization.

Of the economies sampled nine of them are from Africa

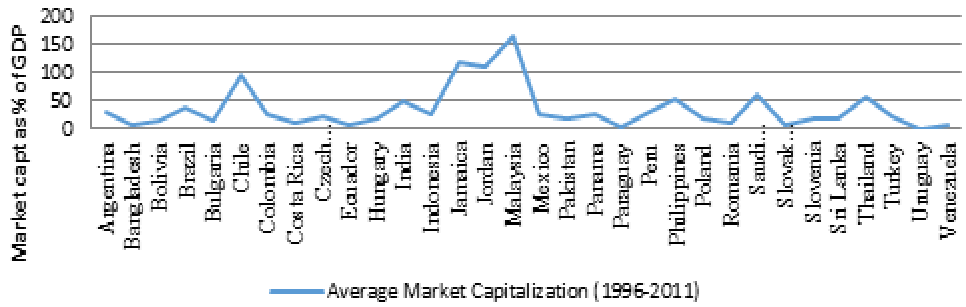

Figure 4. Emerging economies excluding Africa.

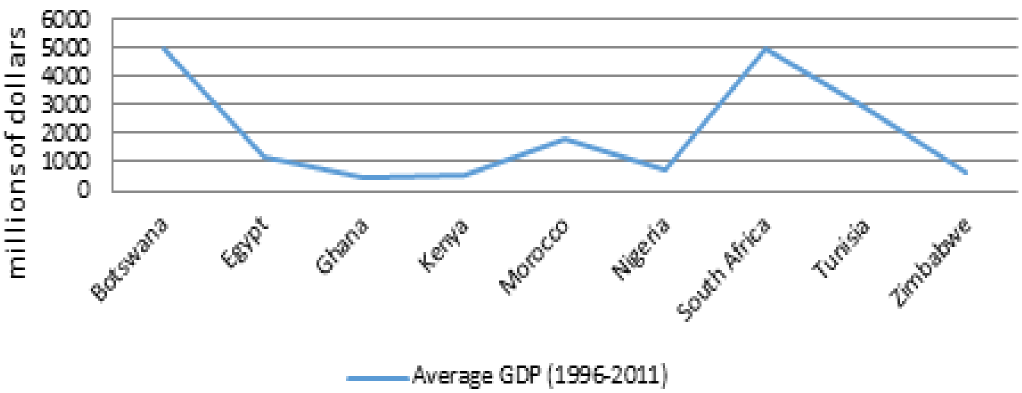

Figure 5. Emerging economies in Africa (GDP).

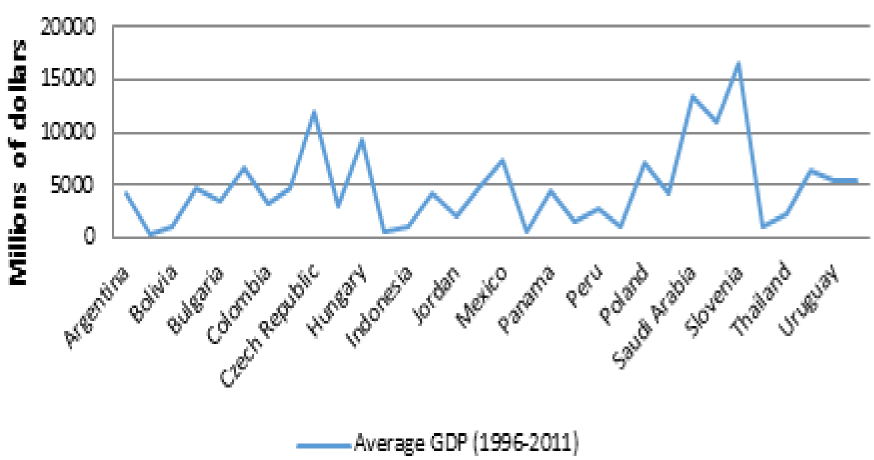

Figure 6. Emerging economies excluding Africa (GDP).

and thirty-two from other continents. Stock market capitalization which is a measure of stock market development had being relatively stable for emerging African economies sampled for this article. The proxy for this measure is stock market capitalization relative to GDP in percentage terms. South Africa and Zimbabwe are the only African economies sampled that have stock market capitalization making more than 50% of their GDP as shown in Figure 3. All the other African countries sampled were below 50% of their GDP.

The market capitalization of emerging stock markets rose from $604 billion to $3,074 billion for the period 1990 to 1999. The trend continued in the 2000 with countries like Malaysia, Jordan, Jamaica, Chile, Saudi Arabia, Thailand, and Philippines accounting for the rise in stock market capitalization as portrayed in Figure 4. In terms of stock market capitalization most of the economies sampled are making less than 50% of GDP. With the African economies sampled economies with high stock market capitalization it is only South Africa, Morocco, and Egypt. Botswana with GDP like South Africa in percentage terms is cited as having low stock market capitalization and Zimbabwe with high stock market capitalization cited with low GDP as shown in Figure 5.

In the case emerging economies outside Africa countries cited with high stock market capitalization are cited in Figure 6 with relatively low GDP. Slovenia with low stock market capitalization is cited here as the country with the highest GDP so is Czech Republic.

EMPIRICAL LITERATURE

Macroeconomic variable and stock market development

It is often argued that stock prices are determined by some fundamental macroeconomic variables such as the interest rate, the exchange rate and the inflation. Fama (1981) highlights that there exists a significant relationship between stock returns and other macroeconomic variables namely: inflation, national, output and industrial production. Stock market-output nexus has also been extensively studied (Habibullah and Baharumshah, 1996; Habibullah et al., 1999). These results indicate that there exists a long run relationship between stock returns and output. The levels of real economic activity, money supply M2, exchange rate and interest rate will likely influence stock prices through its impact on corporate profitability in the same direction. Shiller (1989) argues that changes in stock prices reflect changes in investor’s expectations about future values of certain economic variables that affect directly the pricing of equities.

The link between Capital market development and interest rate has in recent time been an issue among researchers (Ologunde et al., 2006; Anthony and Kwame 2008). It is asserted that the financial structure of a firm, that is, the blend of debt and equity financing, changes as economies develop. It moves towards equity financing through the stock market. If the rate of interest paid by banks to depositors is increased, investors will patronize the banks the more and fewer investors will invest on the capital market. This will lead to a decrease in capital investment in the economy. Hence, stock market performance and development will be lowered because the allocation of capital resources plays a crucial role in the determination of the rate of the nation’s output.

Osei (2006) investigates both the long run and the short run associations between the Ghana stock market and macroeconomic variables. The paper establishes that there is co-integration between the macroeconomic variables and Ghana stock market. The results of the short run dynamic analysis and the evidence of co-integration mean that there are both short run and long run relationships between the macroeconomic variables and the index. In terms of Efficient Market Hypothesis (EMH), the study establishes that the Ghana stock market is information ally inefficient particularly with respect to inflation, treasury bill rate and world gold price.
Kuwornu and Owusu-Nantwi (2011) examined the relationship between macroeconomic variables and stock market returns in Ghana using monthly data. Macroeconomic variables used were consumer price index (as a proxy for inflation), crude oil price, exchange rate and 91-day Treasury bill rate (as a proxy for interest rate). Full information maximum likelihood estimation procedure was used in establishing the relationship between macroeconomic variables and stock market returns. The empirical findings reveal that consumer price index (inflation rate) had a positive significant effect, while exchange rate and Treasury bill rate had negative significant influence on stock market returns. On the other hand, crude oil prices do not appear to have any significant effect on stock returns.

Eita (2012) investigates the macroeconomic determinants of stock market prices in Namibia. Using VECM econometric methodology revealed that Namibian stock market prices are chiefly determined by economic activity, interest rates, inflation, money supply and exchange rates. An increase in economic activity and the money supply increases stock market prices, while increases in inflation and interest rates decrease stock prices. The results suggest that equities are not a hedge against inflation in Namibia, and contractionary monetary policy generally depresses stock prices.

Fama (1981) argues that expected inflation is negatively correlated with anticipated real activity, which in turn is positively related to returns on the stock market. Therefore, stock market returns should be negatively correlated with expected inflation, which is often proxied by the short-term interest rate. Kaul (1990) studied the relationship between expected inflation and the stock market, which, according to the proxy hypothesis of Fama (1981) should be negatively related since expected inflation is negatively correlated with anticipated real activity, which in turn is positively related to returns on the stock market.

Spyrou (2001) also studied the relationship between inflation and stock returns but for the emerging economy of Greece. Consistent with Kaul (1990) results, Spyrou (2001) found that inflation and stock returns are negatively related, but only up to 1995 after which the relationship became insignificant. Kyereboah-Coleman and Agyire-Tettey (2008) used cointegration and the error correction model techniques to show how macroeconomic indicators affect the performance of stock markets by using the Ghana Stock Exchange as a case study. The findings of the study reveal that lending rates from deposit money banks have an adverse effect on stock market performance and particularly serve as major hindrance to business growth in Ghana. Again, while inflation rate is found to have a negative effect on stock market performance, the results indicate that it takes time for this to take effect due to the presence of a lag period; and that investor's benefit from exchange-rate losses as a result of domestic currency depreciation.

Chow et al. (1993) using monthly data for the period 1977 to 1989 found no relationship for monthly excess stock returns and real exchange rate returns. When repeating the exercise, however, with longer than six months horizons they found a positive relationship between a strong dollar and stock returns.

METHODOLOGY

Theoretical models

Macroeconomic variables and investment

One way of linking macroeconomics variables and stock market returns is through arbitrage pricing (APT) (Ross, 1976). The *q* approach to the transmission mechanism increases the macroeconomic significance of stock markets which now take on an important role in managing the process of capital accumulation. APT focused on individual security returns (for selection of relevant studies see Fama, 1981, 1990; Fama and French, 1989; Schwert, 1990; Ferson and Harvey, 1991; Black et al., 1997). It is also used in an aggregate stock market framework, where a change in a given macroeconomic variable could be seen as reflecting a change in an underlying systemic risk factor influencing future returns. Most of the empirical studies on APT theory, linking the state of the macro-economy to stock market returns, are characterized by modeling a short run relationship between macroeconomic variables and the stock price in terms of first difference, assuming trend stationarity (Andrew and Peter, 2007).

Portfolio optimization problems under partial information are becoming more and more popular, also because of their practical interest. They have been studied using both major portfolio optimization methodologies, namely Dynamic Programming (DP) and the "Martingale Method" (MM). While DP has a longer tradition in general, also MM has been applied already since some time for the cases when the drift/appreciation rate in a diffusion-type market model is supposed to be an unknown constant, a hidden finite-state Markov process, or a linear-Gaussian factor process. Along this line are the papers Lakner (1995, 1995), and more recently Sass and Haussmann (2004). We consider the portfolio maximization problem under a hidden Markov setting, where the coefficients of the security prices are nonlinearly dependent on economic factors that evolve as a k-state Markov chain.

No satisfactory theory would argue that the relation between financial markets and the macroeconomics is entirely in one direction. However, stock prices are usually considered as responding to external forces. By the diversification argument that is implicit in capital market theory, only general economic state variables like inflation, money supply exchange rate and GDP will influence the pricing of large stock market aggregates.

Empirical models

Macroeconomic variables and stock market development

For the purpose of this empirical study, the unit of analysis is the 41 emerging economies stock market. Here, we will draw upon theory and existing empirical work as a motivation to select a number of macroeconomic variables that we might expect to be strongly related to the real stock price. The real stock price depends upon the expected stream of dividend payments and the market discount rate. Hence, any macroeconomic variable that may be thought to influence expected future dividends and/or the discount rate could have a strong influence on aggregate stock prices. The macro-economic variables selected as explained under theoretical model of this article are; money supply (MS), consumer price index (CI) and foreign exchange rate in US dollars (EXCH). The objective here is to test the effect of economic growth measured by GDP, and macroeconomic variables (MS, CPI, and EXCH) on stock market capitalization of emerging economies. In this paper, we will draw upon theory and existing empirical work as a motivation to select a number of macroeconomic variables that we might expect to be strongly related to the real stock price.

In this study, the model used by Sangmi and Mubasher (2013) was adopted and modified. In this empirical chapter least squares regression is again considered due to the numerous advantages that it has over other estimation techniques. The analytical model for the macroeconomic determinants of stock market performance is depicted by the modified model of Sangmi and Mubasher (2013).

$$\mathrm{SMC}_{it} = \beta_0 + \beta_1 \mathrm{GDP}_{it} + \beta_2 \mathrm{MS}_{it} + \beta_3 CPI_{it} + \beta_4 \mathrm{EXCH}_{it} + \varepsilon_{it} \quad (1)$$

Where SMC_{it} is the stock market capitalization relative to $\mathrm{GDP}_{i,t}$. $\mathrm{SMC}_{it} = \frac{(\mathrm{SMC}_{it} - \mathrm{SMC}_{it-1})}{GDP_{it}} \times 100$, where SMC_{it-1} is the yearly growth rate of stock market capitalization relative to $\mathrm{GDP}_{i,t}$, at the present year (t). $\mathrm{GDP}_{i,t}$ is Gross Domestic Product. It is a proxy for economic development. $\mathrm{GDP}_{i,t} = (\frac{\mathrm{GDP}_{i,t} - \mathrm{GDP}_{i,t-1}}{GDP_{it}}) \times 100$ is the yearly growth rate of GDP relative to $\mathrm{GDP}_{i,t}$, at the current year (t). $\mathrm{MS}_{i,t}$ is the money supply relative to $\mathrm{GDP}_{i,t}$. It is a proxy for banking sector development. $\mathrm{MS}_{i,t} = (\frac{\mathrm{MS}_{i,t} - \mathrm{MS}_{i,t-1}}{GDP_{it}}) \times 100$ is the yearly growth rate of money supply relative to $\mathrm{GDP}_{i,t}$, at the current year (t). CPI_{it} is a proxy for macroeconomic stability. $CPI_{it} = (\frac{CPI_{it} - CPI_{it-1}}{GDP_{it}})\mathrm{x}100$, where CPI_{it} is the yearly growth rate of CPI_{it} at current time (t). $EXCH_{it}$ is a proxy for macroeconomic stability. $EXCH_{it} = (\frac{EXCH_{it} - EXCH_{it-1}}{GDP_{it}})$ x100%, where $EXCH_{it}$ is the yearly growth rate of $EXCH_{it}$ at current time (t).

GDP was interacted with all the other macroeconomic variables one at time to determine the actual effect of these variables on stock market performance. The following models were run and the significance levels were tested at α=0.05 using different Robust OLS and FGLS, respectively.

$$\mathrm{SMC}_{it} = \beta_0 + \beta_1 \mathrm{GDP}_{it} + \beta_2 \mathrm{MS}_{it} + \beta_3 CPI_{it} + \beta_4 \mathrm{EXCH}_{it} + \varepsilon_{it} \quad (2)$$

$$\beta_0, \beta_1, \beta_2 > 1; \quad \beta_3, \beta_4 < 1$$

$$\mathrm{SMC}_{it} = \beta_0 + \beta_1 \mathrm{GDP}_{it} + \beta_2 \mathrm{MS}_{it} + \beta_5 (\mathrm{GDP} \times \mathrm{MS})_{it} + \varepsilon_{it} \quad (3)$$

$$\beta_0, \beta_1, \beta_2, \beta_5 > 1$$

$$\mathrm{SMC}_{it} = \beta_0 + \beta_1 \mathrm{GDP}_{it} + \beta_3 CPI_{it} + \beta_5 (GDP \times CPI_{it}) + \varepsilon_{it} \quad (4)$$

$$\beta_0, \beta_1, \beta_5 > 1; \quad \beta_3, < 1$$

$$\mathrm{SMC}_{it} = \beta_0 + \beta_1 \mathrm{GDP}_{it} + \beta_4 \mathrm{EXCH}_{it} + \beta_5 (GDP \times \mathrm{EXCH}_{it}) + \varepsilon_{it} \quad (5)$$

$$\beta_0, \beta_1, > 1; \quad \beta_4, \beta_5 < 1$$

Where GMS is the interaction of GDP and MS, GCPI is the interaction of GDP and CPI, GEXCH is the interaction and EXCH. The parameters were estimated using OLS technique. The least squares method produces the best straight line. However, there may in fact be no relationship or perhaps a nonlinear relationship between GDP, CPI, MS, EXCH and stock market capitalization hence a straight line is likely to be impractical. We assess how well the linear model fits the data. A model results in predicted values close to the observed data values. The fit of a proposed regression model should therefore be better than the fit of the mean model. It is assumed that the errors or disturbances have the same variance across all observation points. When this is not the case, the errors are said to be heteroskedastic and the model is corrected by using robust standard error to determine the significance of the parameters of interest.

The test of significance (α=0.05) for this model sought to establish the determinants of stock market performance in emerging economies. The inferential statistics such as the Pearson Product Moment correlation coefficient R^2 and the coefficient of determination R of the data set, as well as p-value and F-test statistics were used. The general use of differencing has been found to reduce the possibility of spurious regression results (Philip, 1986). Studies by Adams (1992) and Anyanwu and Udegbunam (1996) conclude that first-differencing achieves stationarity of variables and thus reduces the possibility of spurious results. Based on the suggestions of the aforementioned studies, and to roughly gauge the robustness and consistency of our estimation results, the regression Equation 1 is also estimated in first difference form. Differencing Equation 1 yields the following equations, which gives models 2 to 5. The stationarity of the variables are tested at α=0.05 significance level with the following empirical model, using the following techniques; Dynamic OLS and Newey-West, respectively.

$$\Delta\mathrm{SMC}_{it} = \beta_0 + \beta_1 \Delta\mathrm{GDP}_{it} + \beta_2 \Delta\mathrm{MS}_{it} + \beta_3 \Delta CPI_{it} + \beta_4 \Delta\mathrm{EXCH}_{it} + \varepsilon_{it} \quad (2')$$

$$\beta_0, \beta_1, \beta_2, \beta_5 > 1; \quad \beta_3, \beta_4 < 1$$

$$\Delta\mathrm{SMC}_{it} = \beta_0 + \beta_1 \Delta\mathrm{GDP}_{it} + \beta_2 \Delta\mathrm{MS}_{it} + +\beta_5 (\Delta\mathrm{GDP} \times \mathrm{MS}_{it}) + \varepsilon_{it} \quad (3')$$

$$\beta_0, \beta_1, \beta_2 > 1; \ , \beta_5 < 1$$

$$\Delta\mathrm{SMC}_{it} = \beta_0 + \beta_1 \Delta\mathrm{GDP}_{it} + \beta_3 \Delta CPI_{it} + \beta_5 (\Delta\mathrm{GDP} \times CPI_{it}) + \varepsilon_{it} \quad (4')$$

$$\beta_0, \beta_1, > 1; \quad \beta_3, \beta_5 < 1$$

$$\Delta\mathrm{SMC}_{it} = \beta_0 + \beta_1 \Delta\mathrm{GDP}_{it} + \beta_4 \Delta\mathrm{EXCH}_{it} + \beta_5 (\Delta\mathrm{GDP} \times \mathrm{EXCH}_{it}) + \varepsilon_{it} \quad (5')$$

$$\beta_0, \beta_1, > 1; \quad \beta_4, \beta_5 < 1$$

We estimate the parameters of the linear regression model by the DOLS since it correct serial correlation and endogeneity problems in models.

The dependent variable is the stock market performance. This measure equals the stock market capitalization divided by GDP. The assumption behind this measure is that overall market size is positively correlated with the ability to mobilize capital and diversify risk on an economy-wide basis. This is consistent with Kemboi et al. (2012), Yartey (2008) and Levine and Zervos (1998).

Based on theory underpinnings discussed in the literature reviewed, we hypothesize a positive relation between exchange rate and stock prices. Mukherjee and Naka (1995) and Wongbangpo and Sharma (2002) among others, indicate that both exchange rate levels and changes affect the performance of a stock market. That is currency depreciation will have a favorable impact on a domestic stock market. The opposite should hold when the currencies of the country appreciates against foreign currencies.

The effect of money supply on stock prices can be positive or negative. Since the rate of inflation is positively related to money growth rate (Fama, 1981), an increase in the money supply may lead to an increase in the discount rate and lower stock prices. However, this negative effect may be countered by the economic stimulus provided by money growth, which would likely increase cash flows and stock prices (Mukherjee and Naka, 1995). Following Geske and Roll (1983), Chen et al. (1986), Wongbangpo and Sharma (2002), we hypothesize a negative relation between stock prices and consumer price index (CPI). The levels of real economic activity (proxied by CPI) will likely influence stock prices through its impact on corporate profitability in the same direction: an increase in real economic activity (fall in the consumer price index) may increase expected future cash and hence, raise stock prices, while the opposite effect would be valid in a recession. Consumer price index is used as a proxy for inflation rate. It is chosen because of its broad base measure to calculate average change in prices of goods and services during a specific period. Inflation is ultimately translated into nominal interest rate and an increase in nominal interest rate increases discount rate which results in reduction of present value of cash flows. An increase in inflation is expected to negatively affect the equity prices.

Consumer price index is used to measure macroeconomic stability. Macroeconomic stability may be an important factor for the development of the stock market. It is expected that the higher the macroeconomic stability the more incentive firms and investors have to participate in the stock market. The stock market in countries with stable macroeconomic environment is expected to be more developed. Consistent with previous studies inflation has been used as a measure of macroeconomic stability. Although there is no agreement on the relationship between macroeconomic stability and stock market development, it is argued that higher levels of macroeconomic stability encourage investors to participate in the stock market largely because the investment environment is predictable. Furthermore, macroeconomic stability influence firms profitability, and so the prices of securities in the stock market is likely to increase. Investors whose investments are experiencing a capital gain are more likely to channel their savings to the stock market by increasing their investments, and so this will enhance stock market development. This variable is proxied with consumer price index. The selection of these variables was based upon the present value model (PVM) theory and literature discussed. This study investigates the effect of macroeconomic variables on stock market performance in emerging economies for the period 1996 to 2011.

The technique used to estimate the coefficients of the linear regression model is the least squares method. Although the ordinary least squares (OLS) estimator is consistent in the presence of a serial correlation in the error term and it is well known that the OLS estimator contains the so-called second-order bias. Focus is on the dynamic ordinary least squares (DOLS) estimator instead of fully modified OLS estimators (FMOLS). The Newey-West estimates are also used to correct for the heteroskedasticity and serial correlation in the results.

RESULTS AND DISCUSSION

Descriptive analysis of the variables

Table 1 summarizes the basic statistical features of the data under consideration including the mean, the

Table 1. Descriptive analysis of the variables.

Parameter	Obs	Mean	Std	Min	Max	Skewness	Kurtosis	Prob
SMC	615	391.27	294.24	33.1	1089.2	0.578	2.283	0.001
MS	615	1.41E+08	1.21E+09	2761.33	1.08E+10	0.664	2.331	0.001
CPI	615	114.98	18.18	98.2	214.7	0.598	2.291	0.000
EXCH	615	347.56	1349.48	0.2	11427.7	0.612	2.309	0.002
GDP	615	18.64	12.46	6.12	26.13	0.654	2.394	0.000

minimum and maximum values, standard deviation, kurtosis, skewness, and the Jarque-Bera test for the data in their levels. The study revealed that gross domestic product (billions of dollars) varied mostly followed by consumer price index, money supply (millions of dollars). Money and quasi money comprise the sum of currency outside banks, demand deposits other than those of the central government, and the time, savings, and foreign currency deposits of resident sectors other than the central government. The mean value of MS for the emerging markets sampled for this article is 1.41E+08 million dollars with a standard deviation of 1.21E+09 million of dollars. This implies the changes in MS in emerging markets are very volatile with a minimum growth of 2761.33 to a maximum of 1.08E+10 million dollars over the period under investigation.

Purchasing power parity (PPP) is a theory which states that exchange rates between currencies are in equilibrium when their purchasing power is the same in each of the two countries. This means that the exchange rate between the two countries should equal the ratio of the two countries' price level of a fixed basket of goods and services. When a country's domestic price level is increasing (that is, a country experiences inflation), that country's exchange rate must depreciate in order to return to PPP. In this article we proxy EXCH with PPP. The average EXCH for the period under investigation is 347.56 per US dollar. The huge difference between the minimum EXCH and maximum EXCH explains the high standard deviation of 1349.48.

In general, the precise evaluation of the normal distribution is given by the values of Skewness and Kurtosis. The Skewness show the amount and direction of skew (departure from horizontal symmetry), while the Kurtosis shows how tall and sharp the central peak is, relative to a standard bell curve.

The table also shows that most of the variables skewed positively, which means that there is a lack of symmetry, in other words, there is a deviation from symmetry of the distribution of data set. That is to say the large positive change is more common than large negative change in the variables.

Regarding peakness, the table shows that the excess kurtosis is larger than 3 for stock market capitalization and exchange rate hence the observed distribution has higher peak compared to the normal distribution. These suggest that the distributions of the variables are leptokurtic, that is non-normal. The data set are not exactly normally distributed since their respective mean, mode and median are not exactly the same, but the data was sufficiently appropriate for the purpose of the study. The mode values were not shown in the table due to space. To confirm the accuracy of the normality assumption, the JB statistics and the equivalent p-values were employed. The findings indicated that all variables are rejected at 1%.

The table revealed that all the variables possess the state of normal distribution, except $\mathrm{SMC}_{i,t}$ and $\mathrm{GDP}_{i,t}$ which are moderately skewed to the right. $\mathrm{SMC}_{i,t}$ and $\mathrm{EXCH}_{i,t}$ have kurtosis values of more than three, and the series are called leptokurtic. As for the remaining variables, the values of kurtosis are less than three, and the series are called platykurtic (Bulmer, 1965).

The study results revealed that the volatility of the variables measured by the standard deviation is high for GDP and consumer price index. To confirm the accuracy of the normality assumption, we employed the JB statistics and the equivalent p-values. The findings indicated that all variables are rejected at 1%, except for consumer price index and policy rate at 1%.

Correlation analysis

Although it is not possible to comment on causation, the results reported in Table 2 revealed information on the strength of the relationships connecting the nine macroeconomic variables. It shows strong positive relationship between stock market capitalization and money supply and a negative correlation between consumer price index, exchange rate and market capitalization on the other hand.

These results support the inclusion of these macroeconomic variables in our analysis.

Levine and Zervos (1998) established that measures of stock market development are positively correlated with measures of financial intermediary development. We examine if this complementary relationship exist in emerging economies. Data permitting, we average the data over the 1996 to 2011 period so that each country has one observation per variable. We compute the correlation between stock market development (measured

Table 2. Correlation coefficient of macroeconomic variables and SMC (levels).

Parameter	SMC	MS	CPI	EXCH	GDP	MS×GDP	CPI×GDP	EXCH×GDP
SMC	1.00							
MS	0.647*	1.00						
CPI	-0.454**	0.657	1.00					
EXCH	-0.642*	0.538**	0.655	1.00				
GDP	-0.581*	-0.546**	-0.683*	-0.624*	1.00			
MS×GDP	0.507*	0.463	0.647*	0.389	0.611	1.00		
CPI×GDP	-0.423	0.558*	-0.523*	0.614*	-0.547	0.641	1.00	
EXCH×GDP	-0.619*	0.551**	-0.459	0.597*	-0.691	0.683**	0.573*	1.00

*, **, *** Correlation is significant at 1, 5 and 10% levels, respectively (2-tailed).

by market capitalization) and all the other explanatory variables for this empirical chapter as shown in Table 2.

The correlation analysis reveals that the data sets are highly correlated with each other. $\mathrm{LSMC}_{i,t}$ is found to correlate much more with $\mathrm{LMS}_{i,t}$ and $\mathrm{LEXCH}_{i,t}$ as compared with the rest of the variables. Also notable is that $\mathrm{LMS}_{i,t}$ is highly correlated with both $\mathrm{LCPI}_{i,t}$, and $\mathrm{LEXCH}_{i,t}$. $\mathrm{GDP}_{i,t}$ is found to be highly correlated with $\mathrm{LCPI}_{i,t}$ and $\mathrm{LEXCH}_{i,t}$ respectively. Our finding confirms the work of Demirguc-Kunt and Levine (1996b).

The financial intermediary development and stock market development are complements rather than substitutes. In general, the data sets are highly correlated; meaning a change of one of the variable would result to a substantial change on the other variables which is expected for such macro-economic variables.

Regression analyses and hypothesis testing

However, before the regression analysis, we sought to establish the trend of the four data sets in order to establish the trend of the involved macro-economic variables. For the heterogeneity across the countries and heterogeneous serial correlation structure of error term, we employ three different panel unit root tests. The research considers three statistical tests for testing if each series in each panel are integrated of order one, otherwise known as stationarity test. These tests are Levin et al. (2002) test, Im et al. (2003) test and Hadri (2000) test for stationarity.

The LLC test is employed to test the stationarity of the panel for it allows heterogeneity of individual deterministic effects and heterogeneous serial correlation structure of the error terms, assuming homogeneous first order autoregressive parameters (Chiawa and Asare, 2009). LLC model tests the null hypothesis of the presence of unit roots against alternative of stationarity. Im et al. (2003*)* broadened the LLC test by presenting a more flexible and computationally simple test structure. The IPS test made the estimation for each of the 'i' sections possible. IPS tests the null hypothesis of unit root against heterogeneous alternative hypotheses which specify that some series in the panel are non-stationary. Hadri (2000) test is distinctive from other two tests mentioned for testing the absence of unit roots, that is, variance of the random walk equals to zero. He proposes a parameterization which provides an adequate representation of both stationary and non-stationary variables and permits an easy formulation for a residual based Lagrange-Multiplier (LM) test of stationarity. Here, it is assumed that the time series for each cross-sectional unit is stationary around a deterministic level or trend, against the alternative hypothesis of a unit root.

Table 3 shows the results of panel unit root tests for each variable in the panel at level and at first difference. The results show that all the panels contain unit roots at level. However, at a differenced level, the panels are said to be stationary, though there may be possibility of non-stationary series in a stationary panel as the panel unit root test will not identify the particular series that is not stationary. This is only a drawback of the panel unit root test, nevertheless stronger and higher degree of power is gained in panel setting than in the usual single cross-sectional setting. This is as a result of the combination of information from time series and cross-sectional data which leads to improvement of power of test (Im et al., 2003). The tests are conducted in two folds. First, is carried out with the inclusion of individual effects followed by the inclusion of individual effect plus deterministic time. The results show that some of the panels contain unit root only at the inclusion of time trend while others confirm the presence of unit root at both levels of testing. All the variables are tested at 5% level of significance and the p-values displayed with their corresponding t- statistic in parenthesis. The results from these three tests provide support for treating all the individual series as non-stationary in their levels but stationary in their first differences.

In order to establish whether there exists a relationship between stock markets performance of emerging economies and macroeconomic variables, a regression analysis was conducted where the stock market

Table 3. Results of the panel unit root test (C).

Variable	LLC Test		IPS Test		Hadri Test	
	NT	T	NT	T	NT	T
SMC	0.031(4.53)	0.178(6.51)	0.328(0.426)	0.327(0.457)	0.000(12.177)	0.0304(1.584)
∆SMC	0.0000(4.866)	0.0115(2.431)	0.0000(5.481)	0.0000(4.047)	0.276(0.577)	0.1754(0.781)
GDP	0.047(1.571)	0.048(1.141)	0.341(0.754)	0.304(0.755)	0.000(14.52)	0.000(7.915)
∆GDP	0.0114(2.141)	0.000(3.552)	0.000(5.829)	0.000(5.534)	0.235(0.677)	0.584(0.597)
MS	0.022(4.33)	0.179(0.66)	0.32(0.42)	0.32(0.42)	0.000(13.16)	0.03(1.59)
∆MS	0.000(5.67)	0.02(2.11)	0.000(6.58)	0.000(4.33)	0.28(4.33)	0.19(4.33)
CPI	0.001(-4.87)	0.001(-6.70)	0.212(-0.81)	0.210(-0.81)	0.000(-15.34)	0.000(-9.06)
∆CPI	0.079(-1.42)	0.001(-4.35)	0.212(-6.59)	0.210(-5.28)	0.237 (0.72)	0.70(-0.52)
EXCH	0.175(-2.52)	0.161(-4.63)	0.234(0.34)	0.289(0.283)	0.000(7.91)	0.004(2.28)
∆EXCH	0.000(-6.68)	0.000(-6.75)	0.000(-8.58)	0.000(-6.66)	0.469(0.91)	0.213(2.05)
MS×GDP	0.065(2.12)	0.057(2.23)	0.124(0.34)	0.309(0.231)	0.000(7.91)	0.014(3.98)
∆MS×GDP	0.000(7.42)	0.000(5.23)	0.000(3.34)	0.000(4.347)	0.108(1.83)	0.014(2.22)
CPI×GDP	0.011(-2.03)	0.108(-2.17)	0.077(-2.34)	0.104(-1.166)	0.000(9.37)	0.004(6.93)
∆CPI×GDP	0.001(-4.24)	0.000(-3.12)	0.000(3.764)	0.000(3.443)	0.155(1.91)	0.012(1.27)
EXCH×GDP	0.065(-2.12)	0.057(-2.28)	0.124(1.34)	0.309(0.233)	0.000(7.92)	0.014(3.98)
∆EXCH×GDP	0.000(-3.62)	0.000(-3.08)	0.010(3.67)	0.003(4.64)	0.311(0.371)	0.277(1.98)

p-values and brackets is the t-values, the significance level is α =0.05.

Table 4. Relationship between macroeconomic variables and Stock Market Performance.

SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
GDP	0.090	0.046	1.97	0.029	-0.171	0.915
MS	0.034	0.025	1.36	0.034	-0.057	0.194
C I	-0.097	0.046	-2.11	0.016	-1.225	0.023
EXCH	-0.079	0.059	-1.33	0.018	-1.088	0.178
_cons	1.151	0.436	2.64	0.001	0.898	2.984

Number of obs = 615. F(4, 610) = 49.57. Prob > F = 0.000. R-squared = 0.217. Adj R-Square = 0.216. Root MSE = 0.228.OLS result corrected for heteroskedasticity (levels)

performance is regressed against the four predictor variables; gross domestic product (GDP), consumer price index (CPI), money supply (M2), and exchange rate in dollars (EXCH) using robust standard errors. It is established that least squares method produces the best straight line. However, there may be in fact no relationship or perhaps no linear relationship between the explanatory variables and the dependent variable. By this a straight line model is likely to be impractical. Because of this it is important that we assess how well the linear model fits the data by employing standard error of estimates, coefficient of determination and analysis of variance.

Four predictors were used (GDP, money supply, consumer price index and exchange rate), while the criterion variable was stock market capitalization. It was assumed that the selected macroeconomic variables were the best predictors for stock market performance; if not, then there was need to conduct a further tests in order to eliminate any potential biases to make the OLS regression estimated best linear unbiased estimators (BLUE). According to Addelbaki (2013), in conducting a quantitative research, one of the means of testing objectively the relationship among variables is to engage in an inquiry by having assumptions clearly stated and testing for theories deductively while guarding against bias, controlling for substitute clarifications, and be skillful to generalize and replicate findings.

For Table 4, the relationship between dependent variable (SMC) and independent variables (GDP, MS, CPI and EXCH) were determined. All the variables were not significant at all three traditional significant levels. The F test was significant indicating that the model fits the data set. The relationship was then viewed with MS, CPI and EXCH each at time using models 3. In each of this case also, the interaction effect was also determined.

The relationship between money supply and stock market performance was tested with model 3 as shown in Table 5. The intercept is 3.915 which is the stock market performance when all the independent variables are zero

Table 5. Relationship between Stock Market Performance and Money Supply.

SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
GDP	7.230	3.544	2.04	0.022	6.471	7.945
MS	0.076	0.046	1.66	0.034	-0.057	0.194
MS×GDP	0.047	0.05	0.944	0.021	-0.044	0.084
_cons	3.915	1.201	3.26	0.001	2.898	4.984

Number of obs = 615. F(3, 611) = 57.96. Prob > F = 0.000. R-squared = 0.273. Adj R-Square = 0.246. Root MSE = 0.183. OLS result corrected for heteroskedasticity (levels).

Table 6. Relationship between Stock Market Performance and Consumer Price Index.

SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
GDP	7.54	2.161	3.49	0.001	5.134	8.054
CPI	0.008	0.005	-1.67	0.028	-0.013	0.164
CPI×GDP	-0.003	0.001	-3.75	0.001	-0.074	0.009
_cons	2.931	1.018	2.88	0.001	1.713	3.188

Number of obs = 615. F(3, 611) = 55.82. Prob > F = 0.001. R-squared = 0.233. Adj R-Square = 0.231. Root MSE = 0.158. OLS result corrected for heteroskedasticity (levels).

Table 7. Relationship between Stock Market Performance and Exchange Rate.

SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
GDP	6.72	3.692	1.82	0.032	5.924	7.322
EXCH	-0.053	0.019	-2.84	0.004	-0.225	0.277
EXCH×GDP	-0.048	0.014	-3.43	0.000	-0.782	0.018
_cons	3.967	1.562	2.54	0.001	1.044	4.127

Number of obs = 615. F(3, 611) = 59.13. Prob > F = 0.000. R-squared = 0.308. Adj R-Square = 0.254. Root MSE = 0.113. OLS result corrected for heteroskedasticity (levels).

(0). It is misleading to interpret particularly if zero (0) is outside the range of the values of the independent variables. The relationship between the variable of interest money supply and stock market performance is described by 0.076. For every 100% increase in money supply (MS), stock market performance increases by 7.6%. The sign is as expected. The value of the test statistic t is 1.66 which implies that there is not enough evidence to infer the existence of a linear relationship between the MS and stock market performance. The interaction effect of the MS and GDP is also not statistically significant but there is enough evidence to infer linear relation between GDP and stock market performance.

In model 3, the effect of consumer price index (CPI) on stock market performance of emerging markets is considered (Table 6). This relationship is expressed by 0.008 with standard error of 0.0048 which yield a t-statistic of -1.67 assuming that all other factors are zero. The sign is not as expected. By implication, there is no evidence to conclude that the coefficient of CPI is not equal to zero (0). This may mean no evidence of linear relationship or there is linear relationship but because of the problem of multi-collinearity we fail to reject the null hypothesis.

The interaction effect of CPI and GDP on SMC is significant which implies that the coefficient of CPI when all other factors are zero is misleading since the effect CPI on SMC is also influenced by GDP. To determine the actual effect of CPI on SMC, interesting values of GDP must be plugged in to obtain the partial effect. The mean value of GDP is 18.64, so at the mean GDP, the effect of CPI on SMC is -0.048. The standard error of this coefficient is 0.016 which yields a t-statistic of -2.99. With relation of GDP to SMC, there is still enough evidence to conclude that there is a linear relation between them, confirming the relationship in model 3.

The relationship between exchange rate (EXCH) and stock market performance when all other factors are zero is significant so is the interaction effect of EXCH and GDP as shown in Table 7. This implies the coefficient of -0.053 is not appropriate. The actual effect of EXCH at the mean value of GDP is 0.842 with a standard error of 0.658. This implies there is not enough evidence to infer

Table 8. Correlation coefficient of macroeconomic variables and SMC (differences)

Correlation	$\Delta\mathbf{SMC}_{i,t}$	$\Delta\mathbf{MS}_{i,t}$	$\Delta\mathbf{CPI}_{i,t}$	$\Delta\mathbf{EXCH}_{i,t}$	$\Delta\mathbf{GDP}_{i,t}$
$\Delta\mathbf{SMC}_{i,t}$	1.00				
$\Delta\mathbf{MS}_{i,t}$	0.04**	1.00			
$\Delta\mathbf{CPI}_{i,t}$	-0.09*	0.16**	1.00		
$\Delta\mathbf{EXCH}_{i,t}$	-0.08**	0.14**	0.11*	1.00	
$\Delta\mathbf{GDP}_{i,t}$	0.09**	0.09**	0.09**	0.14**	1.00

The dependent variable is SMC; ** and * denote statistical significance at the 0.01[a].

a linear relationship between EXCH and SMC. The sign is as expected. We test for serial correlation and Heteroskedasticity in the error term in each model using DW. This assumption is formally expressed as E (e_ie_j) = 0 for all $i \neq$ j, which means that the expected value of all pair-wise products of error terms is zero. If indeed, the error terms are uncorrelated, the positive products willcancel those that are negative leaving an expected value of 0. If this assumption is violated, although the estimated regression model can still be of some value for prediction, its usefulness is greatly compromised. The estimated regression parameters remain unbiased estimators of the corresponding true values, leaving the estimated model appropriate for establishing point estimates and the model can be used for predicting values. However, the standard errors of the estimates of the regression parameters are significantly underestimated which leads to erroneously inflated t-values. Because testing hypotheses about the slope coefficients and computing the corresponding confidence intervals rely on the calculated t-values as the test statistics, the presence of correlated error terms means that these types of inferences cannot be made reliably.

A DW test of 0.351 implies the presence of positive autocorrelation in the error term at 5% significance level. That is the error covariances are not zero (0) and this will underestimate the variance of the parameters in the model and also can cause the rejection of the null hypothesis when it is true. Breusch-Pagan is used to test the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. A large chi-square of 37.83 indicates that heteroskedasticity is present. The presence of heteroskedasticity alone does not cause bias or inconsistency in the OLS point estimates. The consequence of this is that the standard errors and t-statistics for the models are invalid. Because the Durbin-Watson statistic is far from 2 (the expected value under the null hypothesis of no serial correlation) and well below the 5% lower limit and upper limits, it is concluded that the disturbances are serially correlated. To address the problem, the variables are made stationary by first difference of all the variables.

Heteroskedasticity has serious consequences for the OLS estimator. Although the OLS estimator remains unbiased, the estimated SE is wrong. Because of this, confidence intervals and hypotheses tests cannot be relied on. In addition, the OLS estimator is no longer BLUE. Put more simply, a test of homoscedasticity of error terms determines whether a regression model's ability to predict a dependent variable is consistent across all values of that dependent variable. For heteroskedasticity, the null hypothesis of constant error variance is rejected. Heteroskedasticity has serious consequences for the OLS estimator. Although the OLS estimator remains unbiased, the estimated SE is wrong.

Because of this, confidence intervals and hypotheses tests cannot be relied on. In addition, the OLS estimator is no longer BLUE.

One possible way to address this problem is just to use heteroskedasticity-robust standard errors. OLS assumes that errors are both independent and identically distributed; robust standard errors relax either or both of those assumptions. Hence, when heteroskedasticity is present, robust standard errors tend to be more trustworthy.

The VIF test was performed in order to measure the extent to which the repressors were related to other repressors and to find out how the relationship affected the stability and variance of the regression estimates. Variance inflation factor of 4.54 shows that model have relatively moderate multicollinearity problem. Severe multicollinearity is problematic because it can increase the variance of the regression coefficients, making them unstable.

The F-probability for the model provides statistical evidence that the macroeconomic variables and their interaction to GDP simultaneously and jointly affect SMC. But a firm conclusion cannot be drawn based on these results because the regression results displayed are based on level, non-stationary data series and could represent a spurious problem. The presence of serial correlation in the error terms invalidate the use of R-squared and adjusted R-squared.

Since the variables under consideration are not stationary, the first differences of the variables are used to confirm the results using DOLS and Newey-West estimation technique. It was also realized that that correlation of first difference of the data series are not significant as shown in Table 8. This reduces the

Table 9. Relationship between Stock Market Performance and Macroeconomic Variables.

SMC	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
GDP	0.077	0.020	3.84	0.000	-0.082	0.109
MS	0.076	0.018	4.13	0.000	-0.011	0.125
CPI	-0.042	0.016	-2.57	0.000	-0.508	0.044
EXCH	-0.056	0.016	-3.61	0.000	-0.116	0.009
_con	-4.677	1.053	-4.44	0.000	-6.287	-3.056

Number of obs = 615. Number of groups = 41. Time periods = 15. Wald $chi^2(5)$ = 865.88. Prob > chi^2 = 0.0000. FGLS corrected for heteroskedasticity and serial correlation (levels).

Table 10. Relationship between Stock Market Performance and Money Supply.

SMC	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
GDP	0.084	0.009	9.45	0.000	-0.014	0.174
MS	0.234	0.084	2.78	0.001	0.895	0.825
MS×GDP	0.013	0.002	6.50	0.000	-0.012	0.064
_con	-3.701	1.102	-3.36	0.000	-4.257	-2.250

Number of obs = 615. Number of groups = 41. Time periods = 15. Wald chi^2 (4) = 768.14. Prob > chi^2 = 0.001. FGLS corrected for heteroskedasticity and serial correlation (levels model 3).

Table 11. Relationship between Stock Market Performance and Consumer Price Index.

SMC	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
GDP	0.051	0.007	7.32	0.000	-0.075	0.123
CPI	-0.105	0.029	-3.63	0.000	-0.527	0.025
CPI×GDP	-0.005	0.001	-3.55	0.001	-0.039	0.044
_con	-14.051	2.192	-6.41	0.000	-16.264	-13.233

Number of obs = 615. Number of groups = 41. Time periods = 15. Wald chi^2 (4) = 974.15. Prob > chi^2 = 0.000. FGLS corrected for heteroskedasticity and serial correlation (levels model 3).

Table 12. Relationship between Stock Market Performance and Exchange Rate.

SMC	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
GDP	0.078	0.009	9.11	0.000	-0.080	0.109
EXCH	-0.035	0.012	-3.05	0.001	-0.195	0.005
EXCH ×GDP	-0.008	0.002	-3.77	0.002	-0.078	0.057
_con	-3.584	0.704	-5.09	0.000	-5.257	-2.250

Number of obs = 615. Number of groups = 41. Time periods = 15. Wald chi^2 (4) = 873.14. Prob > chi^2 = 0.000. FGLS corrected for heteroskedasticity and serial correlation (levels model 3).

possibility of multicollinearity problem. In the analysis the null hypothesis of no autocorrelation and also the assumption of homoscedasticity for all the models discussed is rejected. The method of generalized least squares (GLS) is introduced to improve upon estimation efficiency when var(SMC) is not a scalar variance-covariance matrix. This technique allows estimation in the presence of AR(1) autocorrelation within panels and cross-sectional correlation and heteroskedasticity across panels. Although these conditions have no effect on the OLS method per se, they do affect the properties of the OLS estimators and resulting test statistics. Hypothesis testing based on the standard OLS estimator of the variance covariance matrix becomes invalid.

Using GLS gives the following results as shown in Tables 9 to 12. All the explanatory variables were significant in explaining variations in SMC.

Table 13. Relationship between stock market performance and macroeconomic variables.

SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.225	0.084	2.68	0.000	0.841	0.821
∆MS	0.131	0.038	3.42	0.001	0.014	0.918
∆CPI	-0.385	0.137	-2.81	0.000	-0.754	0.014
∆EXCH	-0.225	0.084	-2.68	0.000	-0.518	0.016

Number of obs = 614. Number of groups = 41. obs per group min = 614. Avg = 614. Max = 614. R-squared = 0.298. Adj R-squared = 0.270. DOLS Results (Difference model 3).

Table 14. Relationship between stock market performance and money supply.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.644	0.241	2.67	0.003	0.174	1.524
∆M	0.042	0.013	3.18	0.001	-0.064	0.141
∆MS×∆GDP	0.001	0.0003	6.50	0.000	-0.019	0.064

Number of groups = 1. Obs per group min = 614. Avg = 614. Max = 614. R-squared = 0.384. Adj R-squared = 0.263DOLS Results on Macroeconomic variables (Difference).

That is modeling heteroskedasticity and autocorrelation in the models, the variables were significant in explaining variations in SMC.

The p-value of Wald test for all the models were significant at all the traditional significant levels.

DOLS estimation of a co-integrated relation

Due to fact that the variables are non-stationary, the first difference of the variables is taken to make them stationary. To account for the problem of endogeneity and serial correlation, DOLS estimator is used. The results of DOLS estimation of model 3 of the difference in variables are shown in Table 13 and its residuals are also given. Wald chi-square of p-value 0.000 implies the model fit the data set. All the explanatory variables are significant in explaining variations in ∆SMC and the signs are as expected.

Table 14 test the effect of ∆MS on stock market performance. This relationship is expressed by 0.42 assuming that ∆GDP and the interaction effect of ∆GDPand ∆MS are zero (0). From the table there is enough evidence to conclude a linear relationship between the first difference of money supply (∆MS) and first difference of stock market capitalization (∆SMC). The interaction effect is also significant which implies the relationship between ∆SM and ∆SMC when all other variables as zero (0) is not appropriate.

To determine the statistical significance of the coefficient of the partial effect of ∆MS on stock market performance there was need to rerun the regression where the interaction variable is replaced with gross domestic product less the average gross domestic product multipled by ∆MS. This gives the new coefficient on ∆MS (the coefficient of partial effect), the estimated effect at gross domestic product of 18.64, along with a standard error. Running this new regression gives the standard error of $\hat{\beta}_1 + \hat{\beta}_3(18.64) = 0.063$ as 0.0235, which yields t = 2.66. Therefore at the average gross domestic product, it is concluded that ∆MS has statistically significance positive effect on stock market performance. An increase in money supply will increase the liquidity in the economy resulting in an increase in the purchasing power of the citizenry. This means that more money will be available not just for consumption but also for investment hence, an increase in stock market performance. Also people tend to demand more when they have more money in their hands and thereby the prices of shares may increase which leads to stock market performances rising. These results support the real activity theorists’ argument that an increase in money supply increases stock prices and vice versa.

There is also enough evidence to infer a linear relationship between ∆GDP and stock market performance for all the three models. Most industries are procyclical in nature, meaning that the firms in the industry do well as the economy does well and vice versa. If ∆GDP is high, the stock prices generally tend to be high as companies are doing better than otherwise. So, ∆GDP is an important determinant of stock prices. The results are in line with the findings of Levine and Zervos (1998), Garcia and Liu (1999), Yartey (2008) and Mishal (2011).

The relationship between consumer price index and stock market performance is significant and expressed by -0.081 when all other explanatory variables in the model are held constant. As shown in Table 15, model 3, the sign of the linear relationship is as expected. That is 100% increase in consumer price index decrease the performance of stock market by 8.1%. There is also

Table 15. Relationship between stock market performance and consumer price index.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf.Interval]	
∆GDP	0.161	0.055	2.91	0.000	-0.022	0.746
∆CPI	-0.081	0.029	-2.77	0.002	-0.235	0.088
∆CPI×∆GDP	-0.062	0.023	-2.64	0.000	-0.741	0.791

Number of obs = 614. Number of groups = 1. Obs per group min = 614. Avg = 614. Max = 614. R-squared = 0.336. Adj R-squared = 0.323. DOLS results on macroeconomic variables (Difference).

Table 16. Relationship between Stock Market Performance and Exchange Rate.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf.Interval]	
∆GDP	0.743	0.283	2.63	0.000	0.277	1.014
∆EXCH	-0.234	0.084	-2.78	0.000	-0.865	0.032
∆EXCH×∆GDP	-0.017	0.006	-2.81	0.000	-0.119	0.048

Number of groups = 1. Obs per group min = 614. Avg = 614. Max = 614. R-squared = 0.294. Adj R-squared = 0.227. DOLS Results on Macroeconomic variables (Difference**)**

enough evidence to conclude that there is linear relationship between the interaction of ∆CPI and ∆GDP and ∆SMC. With the interaction effect being significant then the actual effect of ∆CPI at mean GDP is -0.027 with a standard error 0.0104 which yields at test of -2.64. Therefore at the average ∆GDP, it is concluded that ∆CPI has statistically significance negative effect on stock market performance. The consumer price index is used as a proxy for inflation. In times of inflation, prices are always unstable and rising. Income is therefore devoted for consumption purposes. Savings and investment will therefore be negatively affected hence affecting stock market performance of emerging economies.

The argument that the stock market serves as a hedge against inflation is based on the fundamental idea of Irving (1930), and is known as the Fisher effect. The Fisher effect states that in the long run, inflation and the nominal interest rate should move one-to-one with expected inflation. This implies that higher inflation will increase the nominal stock market return, but the real stock return remains unchanged. Therefore, investors are fully compensated.

Model 3 EXCH of Table 16 test the effect of first difference of exchange rate (dollar) on first difference stock market performance for emerging markets. The relationship is described by -0.017 with standard error 0.006 when ∆GDP and the interaction of ∆GDP and ∆EXCH are zero (0). The inverse relation is as expected. Since the interaction effect is significant, the linear relationship between ∆EXCH and ∆SMC when all other explanatory variables in model is zero is not appropriate since zero is not in the range of values for exchange rate. The partial effect of ∆EXCH at the mean GDP is expressed by -0.022 with a standard error 0.008 which yields a t-statistic of -2.75. Therefore at the average gross domestic product, it is concluded that ∆EXCH has statistically significance positive effect on stock market performance.

There are different theoretical approaches to understanding the relationship between the exchange rate and stock prices. Among these approaches, the two most prominent are the goods market approaches introduced by Dornbusch and Fischer (1980) and the portfolio balance approaches discussed by Frankel (1983). The portfolio balance approach stresses the role of capital account transactions on determining the relationship between the exchange rate and stock prices. This approach postulates a positive relationship between stock prices and exchange rates, with stock prices being the root cause of the relationship.

The results of the study support the hypothesis of a negative relationship between exchange rate and stock market capitalization of emerging economies and is consistent with the findings of Soenen and Hennigar (1988), Ajayi and Mougoue (1996) who have reported a significant, negative relationship between the exchange rate and stock return. However, it contradicts the findings of Maysami and Koh (2000). They explained that a stronger domestic currency lowers the cost of imported inputs and allows local producers to be more competitive internationally. Yip (1996) also explained that a strong exchange rate limits imported inflation and hence is perceived as favourable news for stock market performance. On the other hand, some studies, such as Bartov and Bodnar (1994) found no relationship between stock prices and exchange rates.

The DW test of 0.92; 0.83; 0.74 and 0.94 shows that there is evidence of serial correlation in the error term for Tables 17 to 21. Breusch-Pagan test of heteroskedasticity with chi-square of 36.06 means the

Table 17. Relationship between stock market performance and macroeconomic variables.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.177	0.062	2.84	0.000	-1.041	0.921
∆MS	0.081	0.006	3.14	0.001	-0.91	1.318
∆CPI	-0.058	0.019	-2.96	0.000	-0.10	0.034
∆EXCH	-0.075	0.028	-2.68	0.000	-1.018	0.269

Number of Groups = 614. Number of groups = 41. obs per group min = 614. avg = 614. max = 614. R-squared = 0.351. Adj R-squared = 0.342. Newey-West estimation corrected for heteroskedasticity and serial correlation (difference).

Table 18. Relationship between stock market performance and money supply.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.644	0.241	2.67	0.003	-1.074	1.124
∆MS	0.042	0.013	3.18	0.001	-0.094	0.121
∆MS×∆GDP	0.001	0.003	6.50	0.000	-0.081	0.084

Number of groups = 41. obs per group min = 614. avg = 614. max = 614. R-squared = 0.366. Adj R-squared = 0.354.Newey-West estimation corrected for heteroskedasticity and serial correlation (difference).

Table 19. Relationship between stock market performance and consumer price index.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.161	0.055	2.91	0.000	0.087	0.646
∆CPI	-0.081	0.029	-2.77	0.002	-0. 05	0.038
∆CPI×∆GDP	-0.009	0.003	-2.64	0.000	-0.341	0.199

Number of obs = 614. Number of groups = 41. obs per group min = 614. Avg = 614. Max = 614. R-squared = 0.343. Adj R-squared = 0.337. Newey-West estimation corrected for heteroskedasticity and serial correlation (difference).

Table 20. Relationship between stock market performance and exchange rate.

∆SMC	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
∆GDP	0.743	0.283	2.63	0.000	0.977	1 414
∆EXCH	-0.117	0.042	-2.78	0.000	-0.815	0.382
∆EXCH×∆GDP	-0.021	0.007	-2.81	0.000	-0.119	0.018

Number of Obs = 614. Obs per group min = 614. Number of groups = 41. Avg = 614. Max = 614. R-squared = 0.369. Adj R-squared = 0.358. Newey-West estimation corrected for heteroskedasticity and serial correlation (difference).

null hypothesis of homoscedasticity is rejected. The consequence of this is that the standard errors and t-statistics for the models are valid. The null hypothesis of homoskedasticity at 5% significant level is rejected. Models 3 with 3 ALL, MS, CPI and EXCH for which results are shown in Tables 17 to 21, respectively explain 29.8, 38.4, 33.6 and 29.4% of the variations in stock market performance, respectively. The estimated regression parameters remain unbiased estimators of the corresponding true values, leaving the estimated models appropriate for establishing point estimates and the models can be used for predicting values.

The VIF test of 2.15; 1.94 and 1.77 for models 1 to 4 of Tables 17 to 21, respectively implies that there is not enough evidence to conclude that multicollinearity is present in the models. Hence the model does not affect stability and variance of the regression estimates. In Table 17 the relationship between macroeconomic variables (∆MS, ∆CPI and ∆EXCH) and ∆SMC are established by correcting for both heteroskedasticity and serial correlation using Newey-West technique. The variables in the model are significant and the signs are as expected. The result confirms that there is enough evidence to conclude that there is a linear relationship

Table 21. Unit root test of residuals DOLS.

Residuals	LLC Test		IPS Test		Hadri Test	
	NT	T	NT	T	NT	T
Model 1	0.0000(4.014)	0.0103(3.224)	0.0000(4. 654)	0.0000(3.472)	0.3371(0.609)	0.2551(0.714)
Model 2	0.0000(-3.705)	0.0000(-4.106)	0.0000(-4.322)	0.0000(-4.428)	0.2441(0.354)	0.2374(0.735)
Model 3	0.0000(4.315)	0.0005(2.971)	0.0000(3.722)	0.0001(4.907)	0.2417(0.315)	0.2064(0.452)
Model 4	0.0000(-3.903)	0.0000(-4.044)	0.0000(-4.153)	0.0000(-3.472)	0.1092(1.421)	0.1333(0.941)

Residuals are tested at 5% level of significance and the p –values displayed with their corresponding t- statistic in parenthesis.

between the selected macroeconomic variables and SMC and this relationships are expressed by ∆GDP (0.177), ∆MS (0.081), ∆CPI (0.058) and ∆EXCH (0.075) with associated Newey-West standard errors of 0.062; 0.006; 0.019 and 0.028, respectively assuming all other variables in the model are constant in the case of each. There is also enough evidence to conclude that these variables are significant with the right signs at 5% significant level. The DW test of 1.97 implies that we fail to reject the null hypothesis that errors are serially correlated at 5% significance level. Breusch-Pagan test of chi-square of 0.438 fail to reject the null hypothesis. The results from the unit root tests of LLC, IPS and Hadri conclude that residuals from Newey-West regression are stationary as shown in the table. This implies that the Newey-West regression is not a spurious regression.

In Table 18, the ∆GDP, ∆MS and their interaction on the effect ∆SMC in emerging markets are examined. The linear relationship between the variable of interest MS is expressed by 0.042 with Newey-West standard error of 0.013 assuming that ∆GDP and the interaction of ∆MS and ∆GDP are constant. Since the value does not fall within the range of values for ∆GDP and also the fact that the interaction effect is significant, makes the interpretation of ∆MS tricky. To resolve this problem, we determine the partial effect of ∆MS given average ∆GDP and this coefficient is described by 0.061 with Newey-West standard error of 0.017 which yields t-statistic of 3.47. That is 1% increase in ∆MS given average ∆GDP yields of 0.061% increase in ∆SMC. It is established that ∆GDP complement MS in explaining variation in ∆SMC. The R-squared of 0.366 implies that the model explains 36.6% of the variations ∆SMC. Breusch-Pagan test of a small chi-square 0.457 implies that heteroskedasticity is probably not a problem or at least that if it is a problem it is not a multiplicative function of the predicted values. DW test serial correlation of 2.019 also failed to reject the null hypothesis of no serial correlation. Wald chi-square of 82.3 confirms that the model fits the data set.

The effect of ∆CPI on ∆SMC is expressed by -0.081 with a t-statistic of 2.91. This implies there is enough evidence to conclude that there is negative linear relationship between ∆CPI and ∆SMC assuming that other variables in the model are constant. That is as ∆CPI increases by 1% ∆SMC reduces by 0.081. It is also established that interaction effect has negative effect on ∆SMC. The partial effect of ∆CPI given average ∆GDP is expressed by -0.249 with Newey-West standard error of 0.080 which yields a t-statistic of 3.11. Breusch-Pagan test the null hypothesis that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. A small chi-square 0.297 implies that heteroskedasticity is probably not a problem or at least that if it is a problem it is not a multiplicative function of the predicted values. DW of 1.92 also implies the errors are not serially correlated. Wald chi-square of 77.9 supports that the model fit the data and that the model is able to explain 34.3% of the variations in ∆SMC.

Table 20 examines ∆GDP, ∆EXCH and their interaction on the effect of ∆SMC. The linear relationship between the variable of interest ∆EXCH is expressed by -0.117 with Newey-West standard error of 0.042 assuming that GDP and the interaction of ∆EXCH and ∆GDP are constant. Since the value does not fall within the range of values for GDP and also the fact that the interaction effect is significant makes the interpretation of ∆EXCH tricky. To resolve this problem, the partial effect of ∆EXCH is determined given average GDP and this coefficient is described by -0.51 with Newey-West standard error of 0.170 which yields t-statistic of 2.99. That is 1% increase in ∆EXCH given average GDP yields 0.51% decrease in ∆SMC. The negative coefficient of the interaction variable implies that ∆GDP does not complement the ∆EXCH of the effect on ∆SMC. The R-squared of 0.369 implies that the model explains 36.9% of the variations ∆SMC. Wald chi-square of 69.5 confirms that the model fit the data set. Breusch-Pagan test of a small chi-square of 0.138 implies that heteroskedasticity is probably not a problem. DW test of serial correlation of 2.14 also fail to reject the null hypothesis of no serial correlation, making the regression result efficient and consistent.

Conclusion

Using a sample of 41 emerging stock economies over a period 1996 to 2011, it was discovered that gross domestic product, money supply, exchange rate in dollars and consumer price index are the important determinants of stock market development. Several policy implications can be drawn from this study. The government, in formulating monetary policy, must be aware of the fact that the stock market responds more favorably to an increase in the money supply. Leaders in emerging economies must also be conscious of the fact that stock prices tend to increase when the leaders implements expansionary policy to increase GDP and also depreciate exchange rates.

From the study, it can be observed that there exists a significant relationship between macroeconomic variables and the stock market performance. This relationship can either be positive or negative depending on which variable is being put under consideration. The study therefore recommends that the macroeconomic environment is very important and should be closely monitored to ensure stability. Emerging economies with stable macroeconomic environment enjoy increased activity at the stock market and hence an increased performance. Stock market performance is an indicator to the foreign investors on the stability of the stock market. It is therefore recommended that good measures should be put in place to promote the stock market activities which in turn increases the stock market performance.

It was established that financial intermediary (policy rate), stock market liquidity, exchange rate in dollars and the stabilization variable (consumer price change) are the important determinants of stock market development, while money supply does not prove to be significant. In addition, it was found that financial intermediaries and stock markets are complements rather than substitutes in development process. In order to promote stock market development in emerging economies, it is important to improve stock market liquidity, efficiently control exchange rate, develop financial intermediaries and then control inflation.

The salient conclusions drawn from this study suggest that strong macroeconomic variables are important for the stock market development in emerging country's markets. To reverse the persistent anemic stock market performance trend in emerging economies, both domestic and external policy makers may have to place significant emphases on the maintenance of the voice and accountability, political stability, government effectiveness, rule of law, and control of corruption. The need to stabilize the macroeconomic indicators as well as improving upon the knowledge base of the citizenry is equally important for performance of stock markets in emerging economies. Although the empirical results are intriguing, they warrant further analysis. Much work remains to be done to better understand stock market development.

These findings also have important policy implications for emerging economies in relation to macroeconomic variables. Prudent management of macroeconomic variables can facilitate stock market development.

Rational management of macroeconomic variables ensures greater confidence in the stability of the economy as macroeconomic volatility magnifies the asymmetric information problem. First, macroeconomic variables such as consumer price index, exchange rate in dollars, money supply and GDP all play important role in determining the market performance. Therefore, policy makers have to maintain reasonable fiscal and monetary discipline in order to increase the demand for credit to the private sector, and subsequently influence the stock market development.

Conflict of Interests

The authors have not declared any conflict of interest.

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Appendix 1. Indicators of stock market performance 1996 to 2011.

Country	Total Value Traded (% of ∆GDP)	Stock Market Capitalization (% of ∆GDP)	Turnover ratio (%)	Number of listed companies	∆GDP per capita $
Argentina	3.75	30.10	23.36	135	4285.75
Bangladesh	3.77	5.47	54.44	216	377.21
Bolivia	0.11	14.26	0.97	27	1020.64
Botswana	0.88	23.03	5.38	16	4981.22
Brazil	19.67	38.61	53.21	464	4582.71
Bulgaria	2.08	13.03	13.13	402	3437.66
Chile	12.06	95.18	12.66	252	6669.80
Colombia	2.65	25.02	9.93	117	3295.39
Costa Rica	0.67	9.72	5.29	17	4683.95
Czech Republic	12.64	23.77	53.42	265	11852.47
Ecuador	0.38	7.16	5.20	47	2903.80
Egypt	12.29	34.88	27.11	690	1158.47
Ghana	0.45	15.37	3.29	26	486.02
Hungary	15.57	20.22	66.30	46	9372.58
India	44.04	47.66	103.11	4845	641.97
Indonesia	11.72	26.66	47.89	294	1195.98
Jamaica	3.88	117.63	3.14	39	4178.91
Jordan	39.69	109.20	29.04	169	2135.87
Kenya	1.58	23.49	5.68	55	528.17
Malaysia	68.64	162.95	39.58	748	4919.38
Mexico	8.52	27.38	32.97	168	7468.29
Morocco	7.98	38.12	17.58	60	1796.14
Nigeria	1.73	14.40	8.53	189	684.49
Pakistan	31.50	19.38	167.50	683	631.11
Panama	0.55	24.84	2.75	22	4573.13
Paraguay	0.12	3.37	5.17	54	1558.13
Peru	3.58	31.72	16.37	225	2706.04
Philippines	12.26	51.51	23.53	219	1123.98
Poland	8.11	19.12	61.71	238	7199.95
Romania	1.45	10.79	21.14	2963	4280.12
Saudi Arabia	73.95	61.17	84.02	87	13402.12
Slovak Republic	2.18	5.83	40.82	346	10871.28
Slovenia	2.65	19.63	24.27	65	16522.56
South Africa	60.32	173.05	32.81	534	4990.85
Sri Lanka	2.81	17.92	16.10	227	1103.19
Thailand	44.10	57.64	84.48	424	2401.98
Tunisia	1.68	13.11	12.61	39	2859.05
Turkey	32.11	23.95	135.91	260	6320.72
Uruguay	0.02	0.74	2.77	13	5460.68
Venezuela	1.69	8.57	14.66	74	5462.98
Zimbabwe	9.40	84.05	11.03	70	592.08

Source: WDI.

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