KENYA SCHOOL
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EARLY WARNING INDEX FOR MACROECONOMIC VULNERABILITY IN KENYA

Lydia Ndirangu[2], Conrado Garcia[3], Esman Nyamongo[4], Ciliaka Gitau[5]

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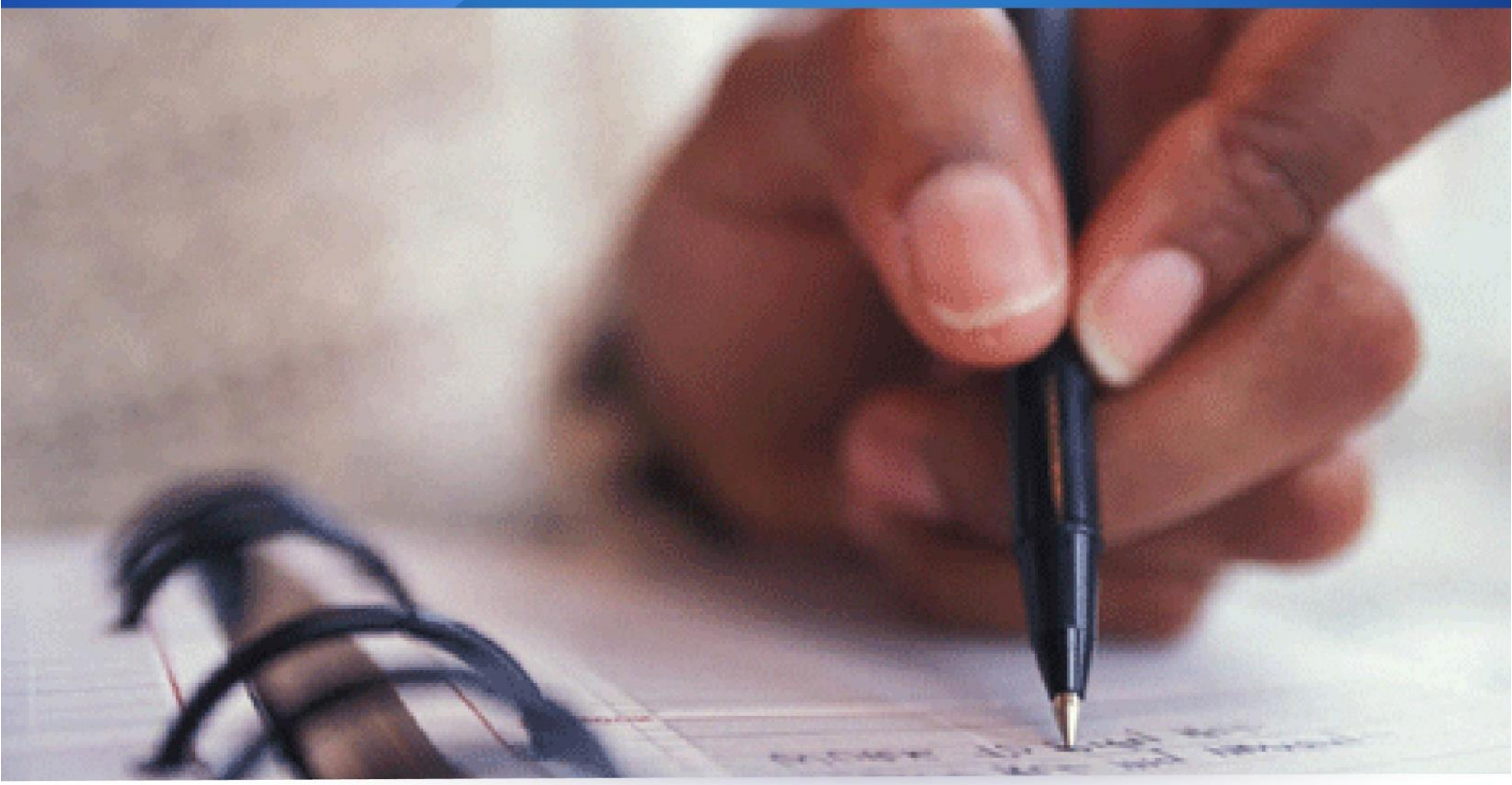

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[2]Corresponding Author, Kenya School of Monetary Studies (KSMS), Central Bank of Kenya, Email: lndirangu@ksms.or.ke
[3]Program Economist, USAID, Kenya;
[4]Central Bank of Kenya
[5]KSMS

Early Warning Index for Macroeconomic Vulnerability in Kenya

Lydia Ndirangu[1], Conrado Garcia[2], Esman Nyamongo[3], Ciliaka Gitau[4]

Abstract

The recent episodes of crisis and shocks make it imperative for countries to develop early warning systems and mitigation measures to enhance their resilience. Many countries, especially developing ones, are yet to develop effective formal frameworks for providing early warning for macroeconomic vulnerability. Kenya is no exception. Monetary authorities often implement ex-post *measures to maintain stability. Such measures can be expensive. The objective of this paper is to develop an instrument that can help to identify situations in which crisis are more likely to occur, and thus aid in design of pre-emptive measures. The paper develops two indices: an index of speculative pressure and an index of macroeconomic vulnerability. The former is used to identify retrospectively, periods of unusual market volatility, while the latter is an ex-ante measure for macroeconomic fragility. To generate signals, thresholds are obtained using: (i) mean plus 1.5 standard deviations, and (ii) the self-exciting threshold autoregressive techniques. A contingency table is used to assess the validity of the "signals approach". The findings are that the framework performs well in predicting periods of macroeconomic vulnerability in Kenya. The real effective exchange rate appears to be the main driver of the macroeconomic vulnerability index.*

Keywords**:** Macroeconomic vulnerability, financial crisis, currency crisis, early warning system, developing country

JEL classification: F31, F31, F47, 016

[1] Corresponding Author, Kenya School of Monetary Studies (KSMS), Central Bank of Kenya, Email: lndirangu@ksms.or.ke

[2] Program Economist, USAID, Kenya;

[3] Central Bank of Kenya

[4] KSMS

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1.0 Introduction

There exists vast literature in the broad framework of poverty analysis on micro level vulnerability. However, less attention has been devoted to the analysis of macroeconomic vulnerability especially for developing countries. Empirical evidence has shown that financial crises have a negative impact on income, poverty and income inequality[5]. As a result, governments tend to put in place measures and institutions to monitor and influence key macroeconomic variables. Although Kenya has no formal framework for detecting macroeconomic fragility, the Government, through the Central Bank of Kenya (CBK) formulates and implements monetary policy directed at achieving and maintaining stability in the general level of prices.

To be able to execute its mandate effectively, the CBK monitors several macroeconomic variables with a view to identifying areas of vulnerability. This paper seeks to develop a formal framework for early warning. This work is motivated by the recent developments in Kenya where the country suffered domestic and external shocks, leading to persistently high inflation and sharp depreciation of its currency. A consistent and effective early warning system (EWS) may have aided in design of pre-emptive measures that raise resilience to such volatility.

An economy being caught unprepared is not new. The global financial and economic crisis that started in 2007 is a good example. Research work on the cause and consequence of this crisis has been unanimous regarding the causes and consequences, and the question regarding whether the economists saw these crises coming is much debated (e.g. Davis and Karim, 2008a). Failure to anticipate such major events provides justification for this current effort in the case of a small open economy.

The rest of the paper is organized as follows: Section 2 examines the performance of key macroeconomic variables and reviews the literature on EWS. Section 3 highlights the key features of the proposed EWS. Section 4 discusses the performance of the proposed framework, while Section 5 concludes.

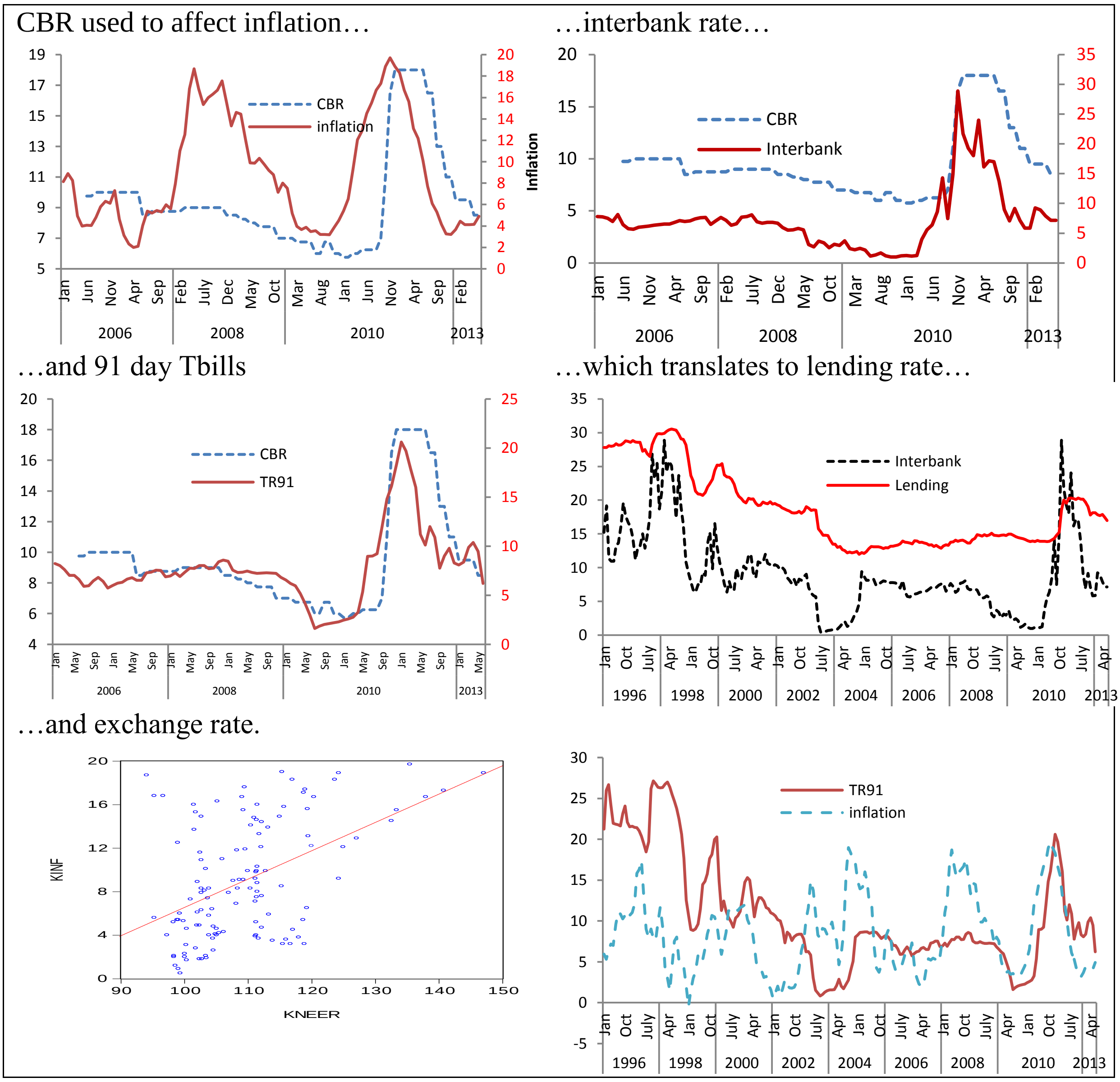
Key macroeconomic variables

[5] Baldacci *et al.*, (2002) find evidence of an increase in poverty associated with financial crises through the slowdown of economic activity, relative price changes, and fiscal retrenchment. The authors find a negative impact on income inequality for some countries in the sample.

The vulnerability of economies has for a long time been relatively unpredictable and monetary authorities all over the world have resorted to ex-post measures to attempt to maintain stability. In Kenya, the Central Bank Rate (CBR) is the key policy variable applied to maintain macroeconomic stability. Other rates such as the treasury bills (TB) rate, interbank rate, lending rate, inflation rate and exchange rate adjust following changes of CBR. Capturing the transmission mechanism is not always an easy and direct exercise, especially in developing economies that are susceptible to external shocks and with a large informal sector. Nevertheless, the charts in **Error! Reference source not found.** show the ovement between the CBR and the short term interests (TB91 and interbank rates) which then affects the long term interest rates (e.g. the lending rate) and eventually inflation and exchange rate.

The policy rate often react ex-post to pressures within the economy. However, ex-post measures can be expensive. This necessitates existence of frameworks that can identify vulnerable periods well in advance to allow for sufficient time for policy makers to put in place counteractive actions to avert a crisis. The analysis in this paper generally follows efforts in the literature such as Kaminsky *et al.*, (1998), Kaminsky (1998) and Herrera & Garcia (1999). More specifically, the paper borrows heavily from the framework developed by Herrera and Garcia (1999).

Figure 1: Stability Mechanism



Source: Central Bank of Kenya

The Kenyan financial sector comprises of banks, insurance companies, stock brokers, investment banks and fund managers. The banking sector in Kenya is relatively more developed compared to the regional economies. It comprises of 44 commercial banks of which 31 are locally owned. There were 1272 bank branches in Kenya by December 2012[6]. Although there is a wide disparity across regions, recent increase in financial innovation especially in mobile banking has seen significant financial sector deepening with the number of banked population rising from about 26 percent in 2006 to 67 percent in 2013.

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[6] CBK, Bank Supervision Report 2012

With respect to the real sector, the service sector contributes about 55 percent of GDP at basic prices, while agriculture and industry contributes 25 and 20 percent respectively. The importance of the real sector and trade financing for transmission of shocks in sub-Saharan Africa is demonstrated by Berman and Martin (2012). They find that Sub-Saharan African exporters are negatively affected through an income effect and a disruption effect (a banking crisis disrupts the financing of trade channels). The disruption effect is much larger and long-lasting for African exporters than for other countries in the aftermath of a banking crisis. Their results suggest that this vulnerability of African exports in the short run comes from their dependence on trade finance. Awoye (2009) also highlights the importance of the real sector in transmitting global crisis. He notes that even though Africa financial markets were not integrated with global financial markets, the international financial crisis effects transmitted through global trade, FDI and portfolio investment inflows, remittances, tourism.

Such findings indicate that consideration of these channels in the construction of an EWS can enhance its performance. This paper indirectly incorporates these channels through the REER since it is trade-weighted.

2.0 Review of Early Warning Systems

Some of the prominent studies that have attempted to develop an EWS for macroeconomic vulnerability include Kaminsky *et al.*, (1998), Herrera and Garcia (1999), Berg and Pattillo (1999), Edison (2003), Kumar *et al.*, (2002) and Bussiere and Fratzscher (2006), which provided a significant contribution in terms of methodologies. Frankel and Saravelos (2010) and Chamon and Crowe (2012) provide a comprehensive review of such studies.

Research work on early detection analysis has a long history. Krugman (1979) developed the idea of 'surpassing a threshold' as an indicator of possible crisis in the future. An EWS should be able to highlight conditions that have been known in the past to be a source of peril to alert the policy makers of potential future crisis (Gramlich *et al.*, 2010). This is based on broad assumptions that the systematic relationships on variables remain stable or similar and ex-ante identification of factors causing a crisis is possible. In addition, proper understanding of a crisis is paramount.

Various approaches have been adopted to predict financial crises. This includes qualitative approach, signal extraction approach, limited dependence approach and duration models

(Gaytan and Johnson, 2002). Most recent approaches, with the technical advancement, include Markov regime switching model (Abiad 2003, Badarinza and Buchmann 2011), artificial neural networks (Frankel and Saravelos, 2010) and econometric approaches (Yiu, Ho and Jin, 2009). Davis and Karim (2008b) assesses the predictive efficiency and indicator robustness of the two main approaches used in the literature to derive EWS — the multivariate logit and the signal extraction methods. Using a panel of 105 countries, they conclude that the use of the multinomial logit model may be better suited to a global EWS whereas the signal extraction approach may be better suited to country specific EWS. This study adopts the non-parametric signal extraction approach based on Kaminsky *et al.*, (1998) and Herrera and Garcia (1999) and improved by Edison (2003).

Kaminsky *et al.*, (1998) developed an index to predict currency and banking crisis. Their composite index is constructed by aggregating signals of the different indicators. Herrera and Garcia, (1999) developed a composite index similar to Kaminsky *et al.*, (1998) but differed in terms of the aggregation process. They constructed an index using aggregation of the individual leading indicators. Once the composite indicator has been developed then it becomes possible to extract crisis signals. Herrera and Garcia (1999) proposed a model with two salient features; the index of speculative pressures (ISP) for identifying periods of unusual market volatility; and a normalized index of macroeconomic vulnerability (IMV) to predict crisis. When the IMV signalled vulnerability, the probability of a crisis was high within a 24-month window, providing sufficient time to put in place counteractive policies.

Nevertheless, this model is not without limitations since the significance of the variables cannot be directly determined. In this regard, out-of-sample period have been used to test statistics, which have been found to perform considerably well (Berg *et al.*, 2005). Seth and Ragab (2012) argue that in the case of developing countries, there is a need for developing country specific case EWS. Even though EWS is perceived as a short run forecasting tool, Krkoska (2000) and Wong *et al.*, (2012) confirm that it is an informative and successful guide to assessment of macroeconomic vulnerability prior to a crisis.

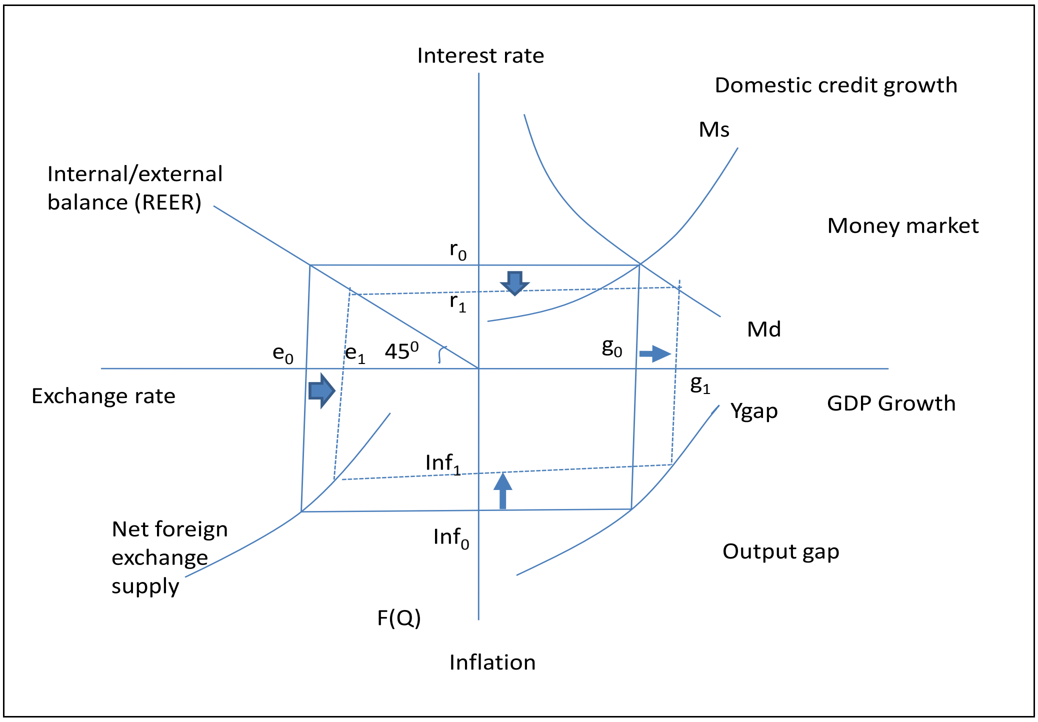
According to Guillaumont (2010) various sources of shocks can lead to varying vulnerabilities while structural conditions will determine the coping measures that can be adopted. Much of the literature has focused on scenarios in developed economies and other regions of the world. There is very limited number of studies focusing on developing countries in Africa on EWS. This study develops an EWS for Kenya. Other studies focusing on developing economies include; Demirguc-Kunt and Detragiache (1998), Guillaumont (2010), Owoye (2009) and Berman and Martin (2012). The latter two concentrate on the channels of transmission of global financial and economic crisis in African economies.

3.0 Methodology

3.1 Conceptual Framework

The logical framework for analysis of macroeconomic vulnerability is shown in **Error! eference source not found.**. To map the macroeconomic vulnerability, considering a short-run model; we use a 4-sector diagram.

Figure 2: Framework of macroeconomic vulnerability



Source: Authors' illustration

Quadrant I shows the money market with the interest rate on the *Y* axis and the GDP on the *X* axis. M_d is the money demand curve which is decreasing in interest rate while the M_s is the money supply curve which is increasing with interest rate. Quadrant II shows the real sector with Y_{gap} being the output gap. High inflation is associated with higher Y_{gap}. Quadrant III is the foreign sector showing how exchange rate interacts with inflation to yield net foreign exchange supply (Dornbusch, 1967, 1983). Quadrant IV is the 45 degree line showing the internal and external balance, which incorporates the fact that there are some external shocks that the monetary policy might not have control over and transmits in the economy through the exchange rate. The assumption is that the economy is operating at below potential and hence an expansionary policy with lower interest rate leads to GDP expansion, and inflation falls as exchange rate appreciates. Similarly if there is a negative external shock, it will cause a depreciation of domestic currency, then an increase in inflation can be experienced which leads to contraction of the economy an increase in the interest rate.

3.2 Data and the Analytical Framework

3.2.1 Data Sources

Data for this study is obtained from the Kenya National Bureau of Statistics (KNBS), Nairobi Securities Exchange (NSE) and CBK. The Inflation data is obtained from KNBS, stock market prices are obtained from NSE, while information on the REER, NEER, 91 days Treasury bill rate, International reserves, domestic credit and money supply is obtained from the CBK.

3.2.2 The Analytical Framework

Two key indicators that seek to warn of the impending crisis are developed: the index of speculative pressures (ISP) and the IMV. The ISP combines movements in three key variables: the nominal exchange rate, the short term interest rate and the international reserves. Though there are many variables that have been suggested in the literature, there is extensive agreement that the three variables are statistically significant in identifying crisis (Frankel and Saravelos, 2010). Additionally, the IMV is a horizontal summation of the real effective exchange rate, real domestic credit growth, M2 as a ratio of international reserves, inflation rate, and the stock market index (Herrera and Garcia, 1999). The full description of the indices is as follows:

3.2.2.1 The index of speculative Pressures (ISP)

Herrera and Garcia (1999) defined a crisis as a period during which the exchange rate falls significantly despite an attempt to prevent the currency depreciation by a sharp increase in interest rates, and/or an official intervention in the foreign currency markets characterized by a large decline in international reserves. The ISP is a simple arithmetic mean following the argument by Eichengreen *et al.,* (1996) that different weights allocated to variables do not have a significant impact on the empirical results.

Here we describe the index that will enable us to identify crises episodes during the period 1996- 2012[7]. The index of speculative pressures (ISP) combines standardized monthly percentage changes in three key variables: the nominal exchange rate, the short term interest rate and the international reserves. This is based on the fact that speculative activities exert pressure on the exchange rate. The central bank may choose to affect the changes in the value of the currency by selling or buying international reserves, so that during periods of depreciation the central bank may run down reserves to defend the value of domestic currency. Furthermore, as shown in the literature (see Eichengreen *et al.*, 1996) the interest rate policy may be used to countervail pressures on the local currency - interest rates have to increase to a level that allows short-term capital to flow into the country to save the domestic currency. The index is defined as follows:

$$ISP = \Delta NER + \Delta TB91 - \Delta IR \qquad (1)$$

Where ISP is the index of speculative pressures; ΔNER is the percentage change in nominal exchange rate; $\Delta TB91$ is the percentage change in 91 day Treasury bill rate; and ΔIR is the percentage change in the international reserves. In constructing this index we normalize each of the components to have a mean of zero and unit variance. This is important to ensure differences in volatility of the different components of the index are equal.

Wide literature exists on variables that can be included in the system and their relative importance, (Eichengreen *et al.,* 1996; Kaminsky *et al.*, 1998; Krkoska, 2000; Abiad. 2003, and Frankel and Saravelos, 2010). Moreover, Frankel and Saravelos (2010) concur that reserves and exchange rate movements are the most statistically significant variables as causes of crises under different techniques, periods and regions and hence, they are highly reliable.

In the adopted signal extraction approach, a signal is said to occur when an indicator crosses a critical threshold. A period of macroeconomic vulnerability is defined as the period during which the index rises above a pre-specified threshold based on the previous observations. In this paper, a crisis period is said to occur when:

[7]The analysis is restricted to the period 1997-2013 because prior to 1997 the data for the key variables in the construction of the index is not available on monthly basis. Even where they are available the new method for the computation of inflation has not been applied to the earlier period.

$$ISP > \mu + 1.5\sigma \qquad (2)$$

Where μ is the sample mean and σ is the standard deviation of the ISP.

Error! Reference source not found. below depicts the pressure periods in the period of nterest. The ISP is constructed using the treasury bill rate while the ISP1 is constructed using the weighted average lending rate of commercial banks as a proxy for short term interest rate. It could have been more appropriate to use money market rate but due data deficiencies this was not achievable. The main objective here is to try and define periods of high market volatility as correctly as possible. The lending rate combined with the exchange rate and international reserves seems to provide better results.

Figure 3: ISP Crisis

Source: Authors'

3.2.2.2 Using the Self-Exciting Threshold Autoregression frameworks

The self-exciting threshold autoregression **(**SETAR) is used to endogenously determine the thresholds. By using SETAR, we avoid the use of a predefined threshold as done above where the threshold is sensitive to the number of standard deviations being selected. SETAR involves estimating an equation of the form below, as described by Ades *et al.*, (1998) and Potter (1995).

$$y_t = \beta_0 + \beta_1 D_t + \beta_2 y_{t-1} + \beta_3 D_t y_{t-1} + u_t \qquad (3)$$

where,

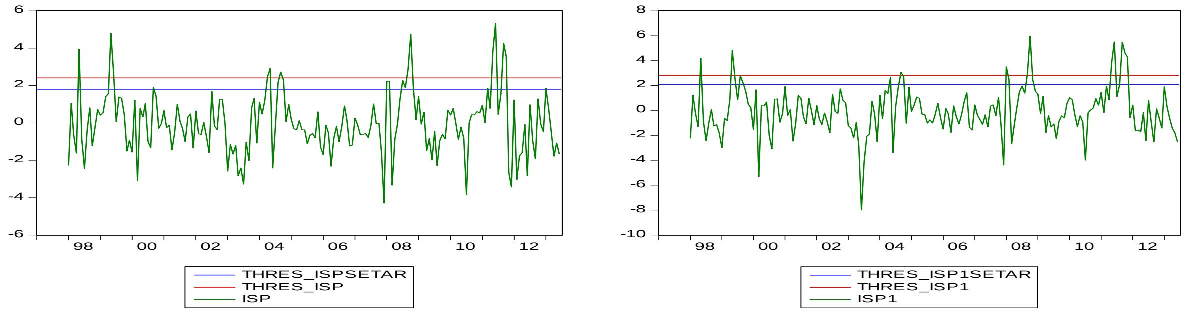
y = ISP (or the IMV)

D = dummy variable that is equal to 1 if y_{t-d} is greater than the chosen threshold at time t-d, where d is a "delay" parameter.

u_t is an independent and identically distributed error term with mean zero and unit variance.

The threshold with the minimum Akaike Information Criterion (AIC) of the regression was chosen. Although the SETAR approach identifies more pressure points, these are around the same pressure periods as with the predefined threshold approach. The many pressure points around the same period can be classified as one crisis. The results are shown in **Error! eference source not found.**. However, the ISP curve touches the SETAR determined ISP threshold in early 2013. This could be indicative of some speculative pressure associated with the general elections in March 2013.

Figure 4: ISP Crisis using SETAR Approach



Source: Author's computation

3.2.2.3 *The Index of Macroeconomic vulnerability (IMV)*

With the identified crisis periods through the ISP, we move on to analyse the behaviour of the leading indicators. To achieve this we use the IMV defined as follows:

$$IMV = REER + DCG + \frac{M2}{R} \qquad (4)$$

Where IMV is the index of macroeconomic vulnerability, REER is the real effective exchange rate; DCG is the real domestic credit growth[8]; M2/R is M2 as a ratio of international reserves. We also augment the simple IMV with the inflation rate, stock market price and the current account balance and test whether the performance of the IMV changes. Inclusion of these additional variables offers additional channels of exchange rate dynamics[9]. The individual variables used in the construction of the index are normalised to have a mean of zero and unit variance.

In the literature there are different ways of extracting the signal from this index: Kaminsky *et al.*, (1998) used the same index as the one developed here but extracts the signal from each of

[8] Real domestic credit is obtained by deflating domestic credit with consumer market prices.
[9] The REER is used as reported by IMF. Inclusion of the current account deficit did not yield significantly different results. This could be due to the fact that much of the information in current account is already captured by REER since the latter is trade weighted.

the individual variables and then the signals from each of these variables are aggregated into a composite index. On the other hand, Herrera and Garcia (1999) follow an alternative way to extract the signal. Here, each of the variables in the construction of the index isnormalised to have a mean of zero and unit variance and then they are aggregated to yield a composite index. This is the index that is used to extract crisis signals. In this paper, we follow the approach of Herrera and Garcia (1999). An extension of the model in Herrera and Garcia also incorporate stock market prices, as done later by Rose and Spiegel (2009).

Once the composite IMV is developed, we need to develop thresholds which will enable one to assess whether the IMV is signalling. In order to accomplish this we apply transformations or filters to the composite index to generate signals using: (1) the Hodrick-Prescott filter (2) the simple long run model and (3) the chartist approach.

Using the Hodrick-Prescott filter, deviations from a long run trend are applied to generate signals. The deviations from trend for each variable are standardized and aggregated to build the IMV. Similar to definition of threshold in ISP, a crisis signal is generated when it surpasses a threshold. In the simple long run model, the IMV is estimated using the variables in levels. In this case, thresholds to generate signals for a crisis are constructed with the conditional standard deviations of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Finally in the chartist approach the IMV is compared with its moving average and a crisis signal is generated when the IMV exceeds the 6-month moving average.

The different approaches generate varying signals and to make a decision on the best fit, a model evaluation criteria is developed as described in the next section. From the set of the three variables; REER, DCG and M2/R, the REER seems to be the main driver of the IMV trend and especially in the simple long run model. The results are shown in **Error! eference source not found.** below. The IMV's includes data up to June 2013. All models generate a signal in June 2013.

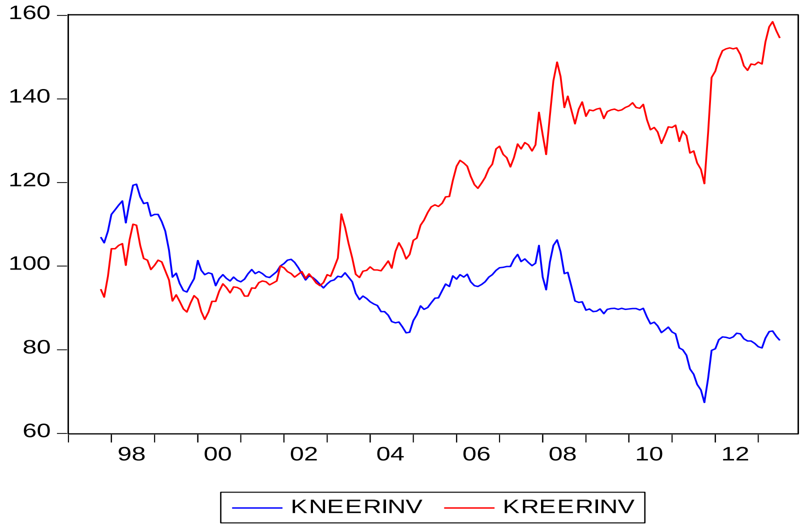
Figure 5: IMV from the three approaches[10]

IMV IMV including SMP IMV including inflation

[10] We also included the current account deficit but found no significant change on the model. This could be due to the fact that much of the information in current account is already captured by REER since the latter is trade weighted.

The signal from the REER could be explained by the growing divergence between NEER and REER as shown in **Error! Reference source not found.**- a reflection of rising inflation ifferential between Kenya and her trading partners since 2004. This change raises possibility of a structural break about this time, which is a possibility given the change in government in 2003. An exchange rate appreciation may lead to deterioration of current account balance (Kappler *et al.*, 2013). Since changes in real and nominal exchange rate can be due to real shocks, monetary policy to correct the imbalance may fail to yield effective results.

Figure 6: Trend of REER and NEER



Source: CBK's data

3.2.3 The evaluation criteria

We use a contingency table in a manner similar to Kaminsky *et al.*, (1998) and Herrera and Garcia (1999) to assess the validity of the signals approach. A signal is emitted if the value of the IMV during a particular period exceeds the threshold value. A signal is said to be valid if it is followed by a crisis within 24 months window. The indicator generates noise, or a false signal, if it emits a signal which is not followed by a crisis within 24 months window. This information is captured as shown in the contingency **Error! Reference source not found.** as ollows:

Table 1: Possible scenarios of signals and crisis

	Crisis within 24 months	No Crisis within 24 months
Signal issued	A	B
No Signal issued	C	D

Error! Reference source not found. is interpreted as follows: Suppose we have an EWS hat is meant to emit a signal on an impending crisis 24 months ahead. We expect a good system to warn or emit a signal 24 months prior to a crisis, as well as in each of the next 23 months, yielding 24 credible signals for the crisis. **Error! Reference source not found.**

nables us to extract useful information to evaluate the performance of the index along the following lines:

(i) Types I and II errors

If Ho= Crisis occurs within 24 months

Ha= No crisis occurs within 24 months

Size of Type I error=P[reject Ho/Ho is true]= Probability of not anticipating a crisis

Size of Type I error= C/(A+C)

Given that the null hypothesis is true (crisis occurs), the perfect signalling device would send 24 signals within a 24-month window. Thus, on the contingency table, a count of 24 would be recorded in Cell labelled 'A'.

Size of Type II error=P[not rejecting Ho/Ho is false]= probability of sending a false signal

Size of Type II error = B/(B+D)

For every non-crisis period, the signals in the 24 month period prior to each crisis are counted and expressed as a ratio of the sum of the no-signal- no crisis (good signals) and the signal – no crisis (false signal), given that no crisis occurred. We complete **Error! Reference source ot found.** by answering the following questions: (1) Does a crisis occur within 24 months and the model did not send a signal? (2) Does a crisis fail to occur within 24 months and the model fails to send a signal? If there is no signal and no crisis we enter a tally in the cell labelled 'D'. A perfect indicator would yield zeros in cells 'C' and 'B'. In reality, however, indicators are not perfect. There will be cases when the indicator will signal a crisis, but nothing happens over the next 24 months. In this case the tally goes to the cell labelled 'B'. Also, there will be occasions when the indicator sends no signal and a crisis occurs, in which case the tally is entered in the cell labelled 'C'.

Next we assess the quality of the index by calculating conditional probabilities with the cell counts in the contingency table. For example, given the occurrence of a crisis within the forecast horizon, one can calculate the percentage of time over which the indicator emitted a signal. In this case we are looking only at the "crisis within 24 months" column of the contingency table to compute the probability that a signal was emitted. This probability is given by A/(A+C). The higher this probability is, the better the index. Alternatively, we may compute the probability of a crisis given that no signal was emitted. This probability is given by C/(A+C); the lower this probability, the better the index. In addition, we need to know how noisy the signal is. That is how frequently the index sends a signal and no crisis occurs. This probability is given by B/(B+D) — the lower the probability, the better.

(ii) The noise-to-signal ratio (NSR)

The signal extraction approach uses relevant indicators to signal a crisis or distress period, if the value of an indicator exceeds a threshold. The threshold value of an indicator is selected to minimize the noise to signal ratio. The Noise-to-signal ratio (NSR) measures the false signals (size of Type II error) as a ratio of the good signals issued (1 - size of Type I error). The smaller the NSR, the better the indicator is at signalling macroeconomic vulnerability. We evaluate the various specifications of the indices by the size of their NSR ratios. A perfect devise should send a signal only when a crisis is eminent but remain silent when no crisis is anticipated. In this case, A/(A+C) = 100% and B/(B+D) = 0%. An index is considered to be good if it minimizes the NSR.

(iii) Probability of a crisis given that a signal was issued P(C/S)

Besides the above criteria, an index is said to be good if it maximizes the probability of a crisis occurring given that a signal was issued.

4.0 Results of the IMV Analysis

The analysis of the ISP identified five periods of excessive market volatility. The identified pressure periods are May 1999; September 2004, January 2008, September 2008; May and September 2011. To assess the performance of the different specifications of the IMV, we first evaluate how often the index sends signals prior to the above periods of market volatility. That is, whether the computed IMV would have assisted in predicting the observed pressure periods. From **Error! Reference source not found.**, it is shown that during the eriod 1999-2011, the deviation model sends a total of 50 signals. It is however, worth noting that during the crisis that started in May and September 2011, it transmitted 12 signals for each crisis. That is, the index was above the threshold in 12 out of the 24-month window.

The simple long-run model on the other hand, generated a total of 97 signals during the sample period. In terms of predicting the May 2011 crisis, it generated a total of 23 signals, only missing one month. As for the September 2011 crisis, it emitted 24 signals one for each month. In addition, the Chartist model sent 55 signals during the sample period, sending 16 signals warning for the May 2011 crisis and 12 signals for the September 2011 crisis. This therefore suggests that of the three models, the simple model was better in sending appropriate signals prior to the 2011 crisis.

Table 2: Comparison of performance

Crisis	Deviations model					Simple model					Chartist model				
	Period before the crisis														
	3M	6M	12M	18M	24M	3M	6M	12M	18M	24M	3M	6M	12M	18M	24M
1999:05:00	3	5	5	5	5	1	2	2	2	2	0	0	0	0	0
2000:02:00	0	0	6	8	8	0	0	1	2	2	0	0	0	0	0
2008:01:00	1	2	5	6	6	3	6	12	18	22	1	3	5	11	17
2008:09:00	0	1	2	4	7	3	6	12	18	24	0	1	3	4	10
2011:03:00	3	6	12	12	12	3	6	12	18	23	0	2	8	12	16
2011:09:00	0	0	6	12	12	3	6	12	18	24	0	0	2	8	12
Totals	7	14	36	47	50	13	26	51	76	97	1	6	18	35	55

Source: Author's compilation

Information available in **Error! Reference source not found.** is used to do further valuation of the different specifications along the following lines: (i) Type I and II errors (ii) the noise-to-signal ratio (NSR) (iii) the probability of having a crisis given that a signal is issued. The outcomes for each specification are shown in**Error! Reference source not ound.**. The first row is the basic IMV. The second row is the basic index augmented with the stock market price (SMP) while the third row adds inflation to the index.

Table 3: Results: 24 month period

	Deviations from Trend Models				Simple models				Chartist models			
	Type I error	Type II Error	Noise/ Signal	P(C/S)	Type I error	Type II Error	Noise/ Signal	P(C/S)	Type I error	Type II Error	Noise/ Signal	P(C/S)
IMV	0.59	0.09	0.23	0.70	0.46	0.06	0.14	0.93	0.68	0.57	1.76	0.48
IMV (incl. smp)	0.43	0.04	0.10	0.94	0.33	0.03	0.09	0.94	0.67	0.65	1.98	0.44
IMV (incl. inflation)	0.65	0.08	0.26	0.63	0.45	0.06	0.18	0.92	0.65	0.56	1.62	0.51

Source: Author's computation

The basic Chartist IMV index reported a higher Type I error at 0.68; the simple model reports 0.46, while the deviations model reports 0.59. Including the stock market price lowers the Type I errors to 0.43 and 0.67 for the deviations and chartist models, respectively and for the Simple long run model to 0.33. Including inflation into the index increases the Type I error of the deviation model to 0.65 from 0.59 for the basic index. That of the chartist model declines slightly to 0.65. This could be interpreted as low information content about the future by the inflation rate. In terms of the Type II error the deviation model and simple long run model reports 0.09 and 0.06 for the basic model while the chartist specifications report the highest at

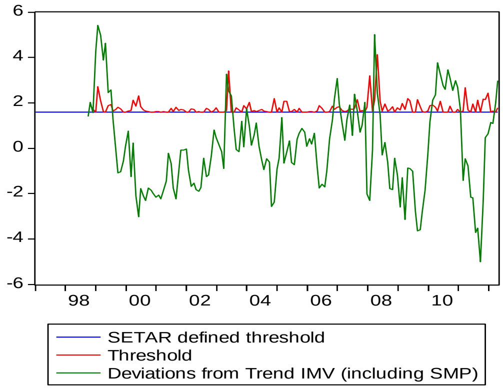
0.57. The Simple long run model where the stock market index is included reports the lowest Type II error of 0.03 while the highest is reported by the chartist model.

Generally the chartist model reports the highest Type I and Type II errors, the highest noise to signal ratio and the least probability of a crisis given that a signal was emitted while simple long run model reports the best statistics given the evaluation criteria. This finding suggests that by making use of the simple long run model, we are capable of predicting the potential pressure periods within 18 to 24 months window with a probability of 0.94, but with a risk of erroneously sending a signal of only 0.03. This makes it the most reliable model. Based on the out-of-sample exercise the simple model consistently signalled prior to the 2011 crisis episode. Type II errors tend to be less costly to a policy maker while Type I error can cause significant welfare costs (Bussiere and Fratzscher, 2006). Moreover, there exists a trade-off between the correct and false signals and the choice of the threshold points might vary depending on the user's objectives. In addition, we use the NSR to measure the suitability of the models to signal crisis, where the model with the lowest ratio is considered to be better.

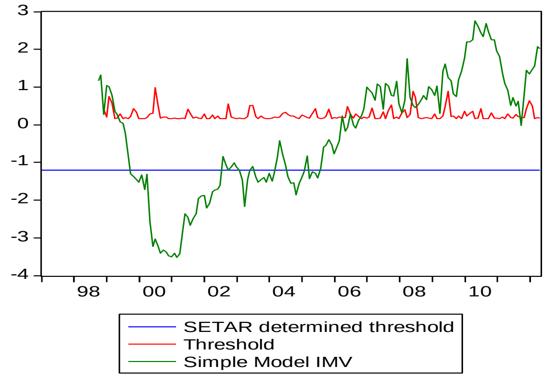
The results indicate a high probability that a crisis will occur given that a signal was generated, which corresponds to a very low Type II error (probability of sending a false signal). This provides a high level of confidence on the early warning index which can be used to complement other information set utilized by the policy maker. From the deviations model the noise to signal ratio ranges 0.10 to 0.26, the simple long-run model reports the ratio at the range of 0.09 to 0.18; while the range for the Chartist model is 1.62 to 1.98. Therefore the chartist model appears to be the worst performing. The simple long-run model, particularly the one with the index including the stock market price is found to be the best in predicting the crisis. Generally, the model including stock market prices seems to outperform the others. In addition stock market prices improve the accuracy of the model significantly and hence, effective monitoring of these variables would inform the possible future economic trends. As mentioned earlier, we make use of SETAR to determine the thresholds endogenously and compare the results with the imposed thresholds. Figure 7 shows that, apart from the basic simple model, the two approaches give almost similar threshold results. The results with SETAR provide support to the ex-ante use of a threshold that uses the mean plus 1.5 standard deviations.

Figure 7: Results from SETAR

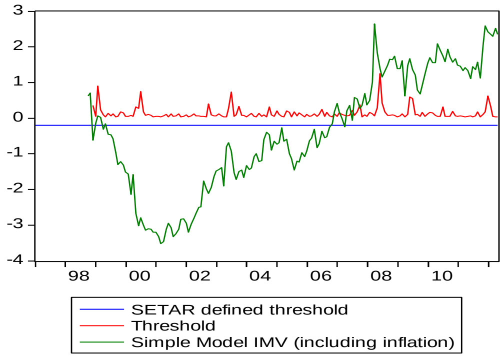
IMV_SMP HP



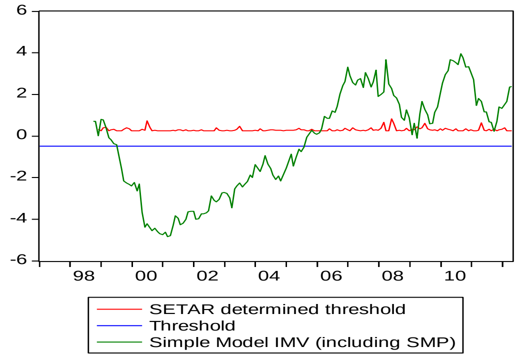
IMV SLR



IMV_INF SLR



IMV_SMP SLR



Source: Author’s computation

The results indicate that the REER and SMP variables are important in determining vulnerability in Kenya. These variables are significantly driven by external factors. The appreciation in REER implies a loss in competitiveness, which can lead to a problem in financing the growing trade deficit. Further, foreign traders form a significant share in the Kenyan stock market which increases the country's vulnerability to short run reversals in capital flows; hence the need for close monitoring.

5.0 Conclusions

This paper aimed at providing a practical early warning tool for Kenya that can be updated regularly at minimum cost to assist policy makers identify ex-ante periods of macroeconomic fragility. Borrowing from past studies, an early warning framework is developed and tested and found to contain significant information that is useful in predicting periods of excessive exchange rate pressure.

An index of speculative pressure is constructed and used for ex-post identification of periods of macroeconomic vulnerability. To test the model, an index of macroeconomic vulnerability (IMV) is developed to facilitate generation of signals to anticipate vulnerable periods. Three approaches are applied to generate the signals: the Hodrick-Prescott, simple long run and the chartist approach. In each of the approaches, the analysis is done for a basic IMV constituting the real effective change rate, real domestic credit growth and broad money (M2) as a ratio of international reserves; the basic IMV is augmented with stock market price and then with inflation. The results show that the simple long run model with stock market prices is the best performing model, reporting the lowest type I and II errors and the highest probability of correct signals. The real effective change rate seems to be the main driver of the IMV. The analysis shows that the simple long run IMV with stock market prices can be useful as an early warning system for Kenya with a lead time of about 18 – 24 months. The results suggest that if Kenya had been using the IMV, it would have been able to anticipate the September 2011 crisis with a probability of 94 per cent. All models send signals from June 2013, indicating an approaching pressure period within the next 24 months. The early detection allows for design and implementation of mitigation measures.

In our analysis, we also find a growing divergence between the nominal effective exchange rate and the real effective exchange rate, especially since 2004. We find that inflation differentials with Kenya's main trading partners have led to the REER appreciation. As inflation is affected by both internal and external factors, this may present challenges as the Central Bank moves towards an inflation targeting monetary policy regime. In addition, REER appreciation implies a loss in competitiveness, which can lead to a problem of financing the growing trade deficit. Furthermore, concerns have been raised related to a REER misalignment, and future work will investigate the possibility of a structural break around this period to shed some light on whether, perhaps, Kenya might be in a different equilibrium, for which a higher real effective exchange rate level may not necessarily mean it is misaligned (overvalued).

Further, as East Africa Community endeavours to establish a monetary union, a study covering the member states would inform on the possibility of common speculative attacks.

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