MODELING LAPSE RISK USING COINTEGRATION AND ERROR CORRECTION APPROACH

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Declaration

CANDIDATE

I declare that this is my original work and has never been presented for any other academic purpose.

Signature... Date..............................

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SUPERVISOR

This project has been submitted for examination with my approval as supervisor.

Signature... Date..............................

Ann Wang'ombe

Dedication

To my beloved Dad, Mum and the entire Keya family, you have been a great encouragement.

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I express profound gratitude to Madam Anne Wangombe (University of Nairobi, School of Mathematics), Dr. Awiti O.J (School of Economics) and all the lectures from the University of Nairobis School of Mathematics; whose invaluable input, incisive analysis, constructive criticism and comments were my source of inspiration.

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Abstract

Policy lapse, in life insurance, is the ratio of the number of policies that default during a period to the average number of policies written within that period. It is a phenomenon that occurs during the activity of insurance operations and one that causes negative effects for those activities: deterioration of business or record insurance losses affecting functionality. Individually closed contracts in life and pensions industry are associated with several risks ranging from underwriting and financial risks to operational risks. This research focuses on one of these risks, more specifically the risk of termination of a policy by the policyholder- the '*lapse*'risk.

This study provided the Error Correction Model as a suitable choice given its key benefits; convenience in measuring the correction from disequilibrium from the previous years'periods and the ability to eliminate trends.

The ECM analysis revealed a long run causality running from all the explanatory variables to the dependent variable. The findings also indicated that the GDP growth and stock market performance affect lapse behaviour in the short run. Impulse response analysis further found that the lapse rate responds far more strongly to the random shocks from the GDP growth than to the shocks from the stock market index. In other words, the GDP growth has a more significant economic impact upon the lapse rate than the stock market index and therefore the emergency fund hypothesis is more favored against the interest rate hypothesis in interpreting the lapse rate dynamics.

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Acronyms and Abbreviations

ADF : Augmented Dickey Fuller

AIC : Akaike Information Criterion

BIC : Bayesian Information Criterion

CBK : Central Bank of Kenya

CE : Cointegration Equation

CUSUM : Cumulative Sum

ECM : Error Correction Model

GDP : Gross Domestic Product

INF : Inflation

IRA : Insurance Regulatory Authority

JKML : Jommo Kenyatta Memorial Library

KNBS : Kenya National Bureau of Statistics

LR : Lapse Rate

NSE : Nairobi Securities Exchange

OLS : Ordinary Least Squares

SMI : Stock Market Index

UR : Unemployment Rate

VAR : Vector Autoregression

WB : World Bank

WDI : World Development Indicators

Chapter 1

INTRODUCTION

1.1 Background

Studies on lapse rates date back to the beginning of the 20th century, when Papps (1919) attempted to forecast lapse rates using an analytical formula. Theories on the influences that variables have on future lapse rates were developed soon afterwards. Well known hypotheses that attempt to explain the lapse behaviour are the emergency fund hypothesis and the interest rate hypothesis.

The emergency fund hypothesis sees insurance as '*an emergency fund to be drawn upon in times of personal financial crisis*'(Outreville, 1990, p.249). Interest rate hypothesis on the other hand suspects interest rates to be an explanatory variable of lapse rates. This school of thought bases that suspicion on the thought that a change in relative profitability of alternative investments might arise from interest rate fluctuation. This hypothesis presumes that the market interest rate is seen as opportunity cost for owning insurance contracts (Kuo, Tsai and Chen, 2003).

Recent studies have shifted to more complex predictors of lapse rates with many published researches demonstrating that macro-economic environment and the characteristics or behaviour of the policyholder and insurance company can all experience a significant association with lapse rates.

Modern insurance policies allow policyholders to choose among a large number of options that can significantly influence the extent of the insurers liabilities (Gatzert, 2009). Policyholders can either surrender their policies, and receive a surrender value (surrender option), or they can opt to discontinue premium payments (paid-up option). The latter refers to a lapse situation.

In traditional parlance, lapse meant termination of an insurance policy and loss of coverage. In the academic literature, however, lapse is often taken to denote both the termination of a policy accompanied by payout of a surrender value to the policyholder and termination without any payment (Kuo et al., 2003)[1] . Lapse and surrender therefore refer to the termination of an insurance contract before maturity. While lapse often refers to the termination of policies without payout to the policyholders, surrender typically indicates that a surrender value is paid out. In this study, a lapse event is said to occur if a personal contract is fully terminated by the policyholder and is non-revivable. All contracts which satisfy these conditions are examined, regardless of the refund.

1.1.1 General Performance of the Global Insurance Market and the Kenyan Case

Global economic growth was about the same in 2013 as in 2012, and still below long-term trends. Among the advanced markets, growth has been strongest in North America, despite a slowdown in the United States, Western Europe returned to slow growth. The emerging markets have had difficult periods given still-weak demand from the advanced economies. Moreover, the announcement of monetary policy normalization by the US Fed sparked financial market turmoil, leading to

[1]Surrender is a terminated policy, like a lapse, but when there is still a cash refund. In which a cash refund refers to a predetermined amount of money which is refunded whenever the contract passes away.

weakness in emerging market currencies and equities. In contrast, advanced markets equities rallied and by end of 2013, long term interest rates in the US and UK were up by over 100 basis points from historically low levels at the end of 2012.

Life insurance growth was not left behind with the growth in the global fronts and, today, accounts for 59.7% of the market value. Global life premiums rose by 5% in real terms over the last three decades reaching USD 2.4 trillion in 2010, or over 3.8% of global GDP. Strong growth in Western Europe and Oceania, in the past decade, has been offset by a contraction in North America and stagnating sales in advanced Asia. Premiums contracted by 7.7% in the US. This was mainly because corporate deals that had boosted growth annuity business in recent years were not repeated. In emerging markets, life premium growth has improved over the years. Life insurance companies are important institutional investors, managing investments in excess of USD 21.5 trillion in 2010, or just about 10% of total global investments.

In the Kenyan Vision 2030 blue print, insurance is considered as one of the economic pillar. Insurance will however be a useful component only if the insurance companies remain more profitable and less risky. And just like any business venture, the longevity and usefulness of life insurance business can only be realized if the various risks are appropriately identified and the appropriate mitigations put in place. In life insurance industry, individually closed contracts are accompanied by underwriting risks such as mortality risk, longevity risk, disability and morbidity risk, life expense risk, revision risk, life catastrophe risk and the lapse risk.

Lapse risk is the risk on which this research is focused and to be specific; it is on the underlying cancellations which, together, are called lapses.

1.1.2 Understanding Risks Which Are Associated with the Life and Pensions Industry

To understand the impact that the lapse rate have on the insurer, this chapter elaborates the risks that insurance agencies face.

The concept of risk can be defined as a change in value, either positive or negative, due to a deviation from the expected value. Risk exists in all facets of an insurance company's operations, as is the case for all organizations. However, for life insurance companies the scope of risk is generally focused into three key risk categories.[2]

1.1.2.1 Life underwriting risk, *generally referred to as technical insurance risk*, relate largely to the risk of a change in shareholder's value due to a deviation of the actual claims payment from the expected amount of claims payments. Life underwriting risks, as seen earlier, can further be sub-divided into seven risk categories as:

Longevity risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level, trend or volatility of mortality rates, where a decrease in the mortality leads to an increase in the value of insurance liabilities.

Morbidity risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level, trend or volatility of disability, sickness and morbidity rates.

Mortality risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level, trend or volatility of mortality rates, where an increase in the mortality rate leads to an increase in the value of insurance liabilities.

[2]all definitions are provided by Solvency II glossary (committee of European Assurance)

Life catastrophe risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from the significant uncertainty of pricing and provisioning assumptions related to extreme or irregular events.

It is important to note, however, that in real life, catastrophes will have a direct effect on profits since settlements will be paid immediately.

Life expense risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level, trend or volatility of the expenses incurred in servicing insurance or reinsurance contracts.

Revision risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from fluctuations in the level, trend or volatility of the revision rates applied to annuities, due to changes in the legal environment or in the state of health of the person insured.

Lapse risk is the risk of loss, or of adverse change in the value of insurance liabilities, resulting from changes in the level or volatility of the rates of policy lapses, terminations, renewals and surrenders.[3]

1.1.2.2 Financial risks, *also referred to as investment/market risk*, include losses due to the reduction in value of investments or returns that are below the planned level. The causes of these losses may be specific to the insurers investment portfolio or a more general market-wide downturn. Financial risks can be categorized into the following risks:

Credit risk is the risk that relates to non-payment of premiums and reinsurance recoveries. It is the risk of a change in value due to actual credit losses deviating from expected credit losses due to the failure to meet contractual debt obligations.

Market risk is the risk stemming from changes in values caused by market prices

[3] All definitions are derived from the Committee of European insurance and Occupational Pensions Supervisors (CEIOPS)(2009) from https://ceiops.org). A complete risk map can be seen under appendix 1.

or volatilities of market prices differing from their expected values.

Liquidity risk is the risk emanating from the lack of marketability of an investment that cannot be bought or sold quickly enough to prevent or minimize a loss. This risk may arise due to illiquidity of assets held to meet the cashflow requirements (commonly referred to as asset or trading liquidity risk), but also due to insufficient funds being available to meet cashflow requirements.

1.1.2.3 Operational risk is the risk of a change in value caused by the fact that actual losses, incurred for inadequate or failed internal processes, people and systems, or from external events, differ from the expected losses. They relate to operational loss events caused by internal or external reasons, excluding all the financial risks that a company has taken on with the expectation of a financial return.

1.1.3 Determinants of Lapse Rate

The observed lapse decision is hypothesized to be explained by combination of variables. Below are the possible explanatory variables that are widely reckoned to explain the likelihood of a policyholder to default in premium payment.

1.1.3.1 Economic explanatory variables

The consideration of gross domestic product, unemployment rate and current yield is borrowed from Kim (2005). However, contrary to Kim (2005) the spread between market interest rate is not considered as single variable. Together with the current yield, both are used as proxies for rates of return.

While the current yield is also used as proxy for the risk-free yield, the credited rate is used as proxy for the internal rate of return constituting a company characteristic.

The stock performance and buyer confidence are also treated as economic explanatory variables.

The detailed variable specification considered is further discussed in Section 3.2.0

i *Gross domestic product (GDP)*

The gross domestic product allows us to assess the overall development of the economy. It is, hence, a good indicator for economic growth (similar to buyer confidence) and is used as a variable to test the emergency fund hypothesis.

ii *Unemployment rate (Ur)*

Information on unemployment has been studied widely in the context of the emergency fund hypothesis, e.g., in Outreville (1990).

iii *Buyer confidence (Bc)*

Data on private spending is used as proxy to assess buyer confidence, i.e., to measure how much money people actually spend for consumption. This can indicate economic growth and can further be used as another indicator beyond unemployment rates to validate the emergency fund hypothesis (see Outreville, 1990).

iv *Current yield (Cy)*

The current yield is calculated as weighted average of treasury bills with a maximum contractual duration of one year. It represents the return of risk-free investments. Its use is discussed widely in the context of the interest rate hypothesis, e.g., in Dar and Dodds (1989).

v *Stock Market performance (SMi)*

A stock investment provides a risky alternative to life insurance savings products. The stock performance thus might provide a starting point for explaining the lapse behavior of policyholders, especially in case of traditional saving and unit-linked products.

Dar and Dodds (1989) explicitly differentiated between internal and external rate of returns in the context of the interest rate hypothesis, but only considered risk-free alternative assets. This approach is extended here to also capture risky assets.[4] The Nairobi Security Exchange 20-share index is used for the analysis. Furthermore, in Kenya the equity market development receives the most public attention and might, hence, constitute an easy alternative investment than the debt instruments.

1.1.3.2 Company specific explanatory variables

Company characteristics are widely used in empirical research on life insurance companies. The consideration of age, distribution focus, legal form and company size is borrowed from Epermanis and Harrington (2006) or Eling and Schmitt (2009). Eling and Kiesenbauer (2011) considered the participation rate spread which constitutes an assessment of the internal rate of return of life insurance products. The detailed variable specifications considered under this category are:

i *Company age (Age)*

A driver for the purchasing decision of insurance customers might be the reputation of the company. Companies that have been in the market for a long period of time have acquired reputation, since they have proven their ability to fulfil long-term contract obligations and their financial stability.

ii *Distributional focus*

Life insurance policies are sold through a variety of distribution channels. The tied agents, banks and broker channels are predominantly used, while the share

[4] Kochanski (2010b) discussed possible specifications of the relationship between lapse rates and capital markets for unit-linked products as well as the existing empirical evidence.

of the direct channel is also recognized.

Additionally, life insurance contracts are also sold through branches and independent agencies.

iii *Legal form (Mutual)*

Generally, the insurance regulation differentiates four legal types of insurance companies:

(a) stock corporation, (b) mutual insurance cooperation, (c) insurance company under public law, and (d) subsidiary of foreign insurance company.

Since the number of insurance companies under public law and subsidiaries of foreign insurers is limited and most of them operate as stock corporations, an insurer is categorized as being a mutual company or not.

iv *Company size (Size)*

Company size is measured by the amount of gross premiums written. Depending on the public perspective, the company size may inspire confidence and play a major role in determining a policy lapse or lack of it.

v *Participation rate spread (Spread)*

The surplus participation mechanism is complex and may only apply to saving products, i.e., endowments and annuities. The yearly declaration of the participation rate takes into account the entire business operation and represents a measure for the internal rate of return (on the saving component of the premium). In accordance to Dar and Dodds (1989), the participation rate is, hence, used to test the interest rate hypothesis.

1.1.3.3 Contract Specific variables

These variables are contract dependent. They include type of product, age of the contract, lifetime of the contract, premium frequency, premium size, sum assured and surrender charge.

Other variables that are closely associated with this class of variables are the reference market rate, optimal moment of lapsation and saving premium (investment made by policyholder).

1.1.3.4 Policy holder Specific variables

The variables closely associated with policy holder characteristics include the age of the policy holder, gender, widowed and marital status. Others are postal code*, new legislation*[5] and mortality rate.

Information on company specific characteristics is rarely found in empirical literature, probably due to problems with data availability. For this reason and for the sake of simplicity and the need to assess the aggregate lapses; this research focused only on the economic variables and their influence on the lapse behaviour, save for the buyer confidence whose data is not publicly available.

1.2 Problem Statement

Policyholders may exercise their right to terminate a contract; this event is called a lapse. Policies that lapse at early stages present the insurance company with inadequate premium to cover the policy expenses. Indeed the option to lapse can, according to Grosen and Jorgensen (2000), account for up to half of the contracts fair value under certain conditions.

Unlike the insurer that originates the life insurance policy contracts, the owner of a life insurance policy has the option to lapse or surrender the life insurance policy at any point in time. This ability to readily lapse a policy can however adversely impact the financial solvency of an insurer if the lapse activity is greater

[5]* indicates that the variable is not mentioned in articles but is expected to be relevant.

than expected; or where a large proportion of policyholders decide to lapse their policies at the same time.

The risks arising from policy lapses[6] are of high economic importance for various reasons. A massive lapse event can threaten the insurers liquidity and impair the operations of an insurance company in a number of different ways. For instance, insurers typically incur the greatest proportion of policy expenses through the acquisition of new business (e.g. commissions, policy issuance costs, administrative costs among others), where it can often take years before the insurer fully recoups those costs. If a policyholder lapses a policy before those costs can be recouped, the insurer must find a way to recover these costs. The same can also lead to losses of potential future profits; specifically, early lapses could result in substantial losses if the insurer is not able to retrieve acquisition costs (Prestele, 2006). Excessive policy lapsation can influence pricing when lapses are greater than expected or when they cause actual mortality rates experienced by the insurer to deviate from expected mortality rates (Doherty Singer, 2002; Gatzert et al, 2009). Moreover, the option to lapse can enhance adverse selection with respect to mortality and morbidity as customers with adverse health are less likely to lapse their contracts, especially where policies can lapse without incurring lapse fees and thus diminish the effectiveness of risk pooling thereby exerting negative effects on the insurers reputation. Extreme policy lapses and surrenders could result in situations where the insurer must liquidate high-yielding investments in order to satisfy policyholder requests for surrender values.[7]

Lapsation is therefore of interest not only to academicians, but also highly relevant

[6] Lapse risk covers all legal or contractual policyholder options which can significantly change the value of the future cashflow. This includes options to fully or partially terminate, decrease, restrict of suspend the insurance cover as well as options which allow the full or partial establishment, renewal, increase, extension of resumption of insurance cover.

[7] This potential problem associated with policy surrender assumes that the policy is a whole life insurance policy and that the cash value that has accumulated within the policy (if any) exceeds surrender.

for the industry, regulators and policy makers. The risks that surround policy lapses are problems to the insurance industry players and in order to mitigate their negative effects, it is important for insurance companies to develop reliable models that will help in predicting the lapse behaviour.

1.3 Objectives of the Study

1.3.1 General Objectives

The broad objective of this study is to construct a robust lapse risk model that accurately specifies the lapse behaviour.

1.3.2 Specific Objectives

To re-examine the contending lapse rate hypotheses: the emergency fund hypothesis and the interest rate hypothesis.

To achieve this objective, we will:

(a) Specify a statistical model underlying the objectives; and

(b) Estimate the model parameters specified in (a).

1.4 Justification of the Study

The need to determine a predictive model for lapse rates calculations to aid in the pricing of insurance and forecasting of cashflow necessitated this study. The study will seek to understand how lapse rate has been responding to changes in the various macro-economic variables.

The goal of this research is to find those variables which are seen as significant drivers of lapse rates and to develop a model that will fit for forecasting with those variables.

Chapter 2

LITERATURE REVIEW

Insurance industry players have an objective function which they want to maximize or minimize depending on the nature of that function. There is wide agreement about the role that premium lapses play; influencing the prices of contracts, necessary liquidity of an insurer and the regulatory capital which should be preserved.

There is even wider agreement about the risks that lapses pose to the insurance industry, i.e. the risks due to changes in value caused by deviations from the actual rate of policy lapses from their expected rates.[1]

2.1 Theoretical Literature

There are various theoretical approaches to understanding lapse rate in the insurance set up. These are: the Emergency Fund Hypothesis, the Interest Rate Hypothesis, Policy Replacement Hypothesis and the Rational Policyholder Hypothesis.

[1] These types of lapses together encompass policies cancelled or renewed by policyholders or insurers regardless of the surrender value.

2.1.1 The Emergency Fund Hypothesis

This school of thought claims that personal financial distress forces policyholders to lapse their contracts in order to access the surrender value. Different indicators are used for personal distress, such as (transitory) income and unemployment. Dependent on the scope, these variables are denoted as macro-economic characteristics, using Gross Domestic Product (GDP) and national unemployment rate as proxies.

They argue that individuals will be more likely to lapse a life insurance policy when faced with economic hardship and that this decision may be due to:

a) a desire to use the funds that would otherwise go to premium payments for other important needs; and

b) a desire to take advantage of any cash value that has accrued within the policy to cover various household expenses.

2.1.2 The Interest Rate Hypothesis

These proponents maintain that lapse rates are negatively related to internal rates of return (such as surplus participation) and positively related to external rates of return (such as market interest rates or stock returns).

They contend that, in the eyes of the investor, the opportunity cost rise when the market interest rate increases and that a rise in interest rates will decrease the equilibrium premium, the premium which is seen as adequate under present interest rates, and consequently increase the likelihood that a similar contract can be obtained at lower costs. The policyholders may therefore be willing to remove funds from a life insurance policy (either by way of loan or surrender) in order to take advantage of higher market rates.

2.1.3 The Rational Policyholder Hypothesis

Next to the traditional hypotheses, some new and less popular hypotheses have been developed. One of these is the rational policy holder hypothesis which is based on the thought that there is a reference market rate at which it is optimal to lapse a policy.

The hypothesis is quite similar to the interest rate hypothesis with the major difference being in the chosen representation of the response variable. The interest rate hypothesis outcome is continuous, which was the likelihood of a lapse, while the rational policyholder hypothesis models lapses as being either optimal or not; making the response variable binary.

2.1.4 The Policy Replacement Hypothesis

The policy replacement hypothesis amounts to the assumption that policy lapses may occur simply because the policyholder has identified a more attractive policy with better terms or rates.

Under this hypothesis, one anticipates a positive relationship between new life insurance business and policy lapses, as individuals allow a policy to lapse for the explicit purpose of purchasing a new life insurance policy.

Whereas GDP, unemployment rate, interest rate and the NSE 20-share index can be selected as explanatory variables, it is often a combination of variables that is used for predicting lapse rates. Recent studies have achieved high predictive power by applying completely different sets of variables; Milhaud et al. (2010) achieved an accuracy of 90%; whereas Briere-Giroux, Huet, Spaul, Staudt and Weinsier (2010) indicate that their model achieved an even higher accuracy. In their studies, the authors used variables such as gender, premium frequency, premium size, surrender rate and the value of the insurance.

2.2 Empirical Literature

Considerable volume of empirical work has been carried out by many researchers in trying to establish which of the hypotheses; emergency fund, interest rate, rational policyholder and policy replacement hypothesis best explains the changes in lapse rate.

Over the past twenty years, empirical investigations into the motives for policy lapses have generally reported evidence supporting the emergency fund hypothesis and have also found evidence consistent with the policy replacement hypothesis. As alluded to earlier, these studies are typically conducted using aggregate (macroeconomic) data to test the different hypotheses.

Outreville (1990), using the country-level data for the period 1966 through 1979, studied the emergency fund hypothesis with lapse data of whole-life insurance in the United States of America and Canada and contended that the surrender value of an insurance contract can be seen as an emergency fund in times of personal distress. In each of these studies, the results provide consistent evidence in favour of both the emergency fund hypothesis and the policy replacement hypothesis. Additional support for the emergency fund hypothesis is presented by Kim (2005) and Jiang (2010) using macroeconomic data from Korea and the United States of America respectively.

In order to address the long term lapse dynamics; Kuo, Tsai and Chen (2003) investigated both the emergency fund and the interest rate hypotheses using the data from the United States and cointegration techniques. Their finding was that interest rate effect is economically more significant than the unemployment rate in explaining lapse rates and is more favoured over the emergency fund hypothesis. However, Kiesenbauer (2011) using the company-level German life insurer data found limited support for the emergency fund hypothesis.

Dar and Dodds (1989), using aggregate data on endowment life insurance policies written by British insurers from 1952 through 1985, tested both the emergency fund hypothesis and the interest rate hypothesis considering lapse data for endowment policies in the United Kingdom. They found evidence in favour of the emergency fund hypothesis, but no significant relationship between surrenders and rate of return.

Another aspect which might become more and more relevant in the context of the interest rate hypothesis is the secondary market for life insurance. In this case, market participants or the life settlement providers purchase life insurance policies. With the increasing growth in this market, it might substantially affect future lapse rates. Other relevant aspects that might make the interest rate hypothesis even more relevant in the future are the trends towards lower surrender fees, higher transparency and better information of the policyholders.

Although much of the empirical research that has examined the above hypotheses with respect to lapses has relied on macroeconomic data, some recent studies have used microeconomic data. For example, Liebenberg, Carson and Dumn (2012) employed household-level data from the Survey of Consumer Finances (SCF) longitudinal panel dataset (between the years 1983 and 1989) to test the factors related to both the demand for life insurance and the decision to drop life insurance. The authors findings were that the decisions regarding life insurance holdings are significantly related to whether one of the spouses recently became unemployed, consistent with the emergency fund hypothesis. They also report evidence in support of the policy replacement hypothesis.

By and large, much of the literature provides fairly consistent support for both the emergency fund and the interest rate hypothesis, it should however be reiterated that the majority of the empirical evidence is provided through the use of aggregate (macroeconomic) data.

Chapter 3

METHODOLOGY

Following the objectives of the study and the hypothesis tested in this study, identification of the variables that affect lapse rate is of paramount importance. Discussion in the previous chapters has identified some of these variables, and the manner in which they are expected to affect the response variable.

3.1 Theoretical Framework

Theoretical models that explain the causes of policy lapses have not been established and therefore the study uses interest rate hypothesis and emergency fund hypothesis in establishing the link between theory and empirical literature.

$$LapseRate = f(stockmarketindex, unemployment, gdp, inflation)$$

Where the stock market index is a proxy for the interest rate hypothesis while the other three variables, i.e. unemployment, GDP and inflation stand for emergency fund hypothesis.

In the long-run:

$$L_t = \beta_0 + \beta_1 SMI_t + \beta_2 UR_t + \beta_3 INF_t + \beta_4 GDP_t + \varepsilon_t \quad (3.1)$$

In the short-run:

$$EC = \Delta L_t + \beta_1 SMI_t + \beta_2 UR_t + \beta_3 INF_t + \beta_4 GDP_t + \varepsilon_t \tag{3.2}$$

Where EC is the error correction specification that helps in modeling the short term effects.

3.2 Model Specification

Since the variables in the model were integrated and cointegrated, an error correction model (ECM) was adopted.

The Basic structure of an ECM:

$$\Delta Y_t = \alpha + \sum_{i=1}^{p} \beta_i \Delta Y_{t-1} + \eta ECM_{t-1} + \varepsilon_t$$

Where ηECM is the error correction component whereby η measures the speed at which prior deviations from equilibrium are corrected, Y_t denotes a vector of variables in the model, α is vector of constants, β denote vector of parameters containing short run information, p is the maximum lag and ε_t is vector of white noise errors.

Equation * denote the model of interest in the ECM

$$\Delta lr_t = \alpha + \sum_{i=1}^{p} \beta_1 \Delta lr_{t-1} + \sum_{i=1}^{p} \beta_2 \Delta smi_{t-1} + \sum_{i=1}^{p} \beta_3 \Delta ur_{t-1} + \sum_{i=1}^{p} \beta_4 \Delta inf_{t-1} + \sum_{i=1}^{p} \beta_5 \Delta gdp_{t-1} + \eta ECM_{t-1}$$

Where the betas ($\beta_i, i = 1,2,3,4,5$) are the short run dynamic coefficients, η denote the speed of adjustment to equilibrium, p is the maximum lag and ε_t is the error term.

3.3 Data Type and Source

This study used secondary time series data covering the period 1964-2013. This period is ideal for the study given that it enables us to capture the behaviour of variables of interest prior to and after financial sector liberalization. The choice of the time domain is therefore influenced by the desire to have a large sample size so that the estimates are unbiased, consistent as well as the desire to determine the effects of the various variables during the period when the global economy is seen to be stable following the recovery from the global recession.

The main sources of data used in this study include:

i) Statistical Abstracts;

ii) Economic surveys;

iii) Central Bureau of Statistics (CBS) publications;

iv) Central Bank of Kenya (CBK) publications;

v) Insurance Regulatory Authority (IRA) Annual reports;

vi) Association of Kenya Insurers (AKI) Annual reports; and

vii) World Bank- World Development Indicators (WDI)

Variable	Definition	Measurement	Data Source	Expected Sign
Lapse Rate (LR)	The rate at which life insurance policies terminate because of non-payment of premiums. When policies are lapsed before enough premium payments are made to cover early policy expenses, the company must make up this loss from remaining policyholders. Therefore, the lapse rate will affect the cost of the policy	%, annual rate	Statistical Abstracts, KNBS	Positive
Stock Market Index (SMI)	A measure of the value of a selection of the stock market computed from the prices of selected stocks (typically weighted average). It is a tool used by investors and financial managers to describe the market and to compare the return on specific investments	%, annual rate	Statistical Abstracts, KNBS	Positive
Unemployment rate (UR)	Is the number of unemployed people as a percent of of the labour force where the labour force includes the people who are either employed or unemployed, but looking for work	%, annual rate	World Bank (WDI)	Positive
Inflation rate (INF)	Annual percentage change to consumer price idex.	%, annual rate	World Bank (WDI)	Positive
GDP Growth (GDP)	The annual growth rate of total market value of final goods and services produced with domestic factors of production	%, annual rate	World Bank (WDI)	Negative

Figure 3.1: **Definition and Measurement of the Variables**

3.4 Data Analysis Technique

The study used error correction model (ECM) in the analysis after testing for stationarity and cointegration. The ECM popularity stems from Engle-Granger representation theorem which states that if two series are cointegrated then they will most efficiently be represented by error correction specification.

The versatility of ECMs give them a number of desirable properties which include the ability to reconcile the short run behaviour of variables with their long term relationships, applicability to both integrated and stationary time series data, ability to model theoretical relationships, the fact that it treats all the variables as endogenous and that it can be estimated using OLS. Eviews statistical software was used to carry out the regression.

3.4.1 Cointegration

As a general rule, nonstationary time-series variables should not be used in regression models, to avoid the problem of spurious regression. However, there is an exception to this rule. If y_t and x_t are nonstationary variables, then we expect their difference, or any linear combination of them, such as $e_t = y_t - \beta_1 - \beta_2 x_t$ to be I(1) as well. There is however an important case when $e_t = y_t - \beta_1 - \beta_2 x_t$ is stationary I(0) process. In this case y_t and x_t are said to be cointegrated.

The basic intuition behind cointegration analysis therefore, is that even though a group of nonstationary variables might individually wander extensively, these variables can be expected to wander in such a way that they do not drift too far apart from one another, given that the difference et is stationary. That is, although individually they are time series with unit roots, a particular linear combination of them is stationary. We outline the definition and estimation procedure for cointegrated vectors as follows.

A (n x 1) vector time series y_t is defined as cointegrated in (d, b) order if each of the series is individually an I(d) process, namely, a nonstationary process with d unit roots, whereas a certain linear combination of the series $a`y_t$ is an I (d-b) process for some nonzero (n x 1) constant vector, a. The vector yt considered in this study contains five variables y_{1t}, y_{2t}, y_{3t}, y_{4t} and y_{5t}; where y_{1t} is the lapse rate, y_{2t} is the stock market index, y_{3t} the inflation rate, y_{4t} is the GDP growth and y_{5t} is the unemployment rate. Suppose that y_t is cointegrated in the (1,1) order; then, according to the Granger Representation, y_t follows an error-correction model of the form:

$$C(L)\Delta y_t = \mu + \gamma y_{t-1} + \varepsilon_t \tag{3.3}$$

where C(L) is a 5 x 5 matrix polynomial in the lag operator L of order p, is the first-order difference operator, is an intercept vector, is a 5 x 5 constant matrix, and et is a white noise error term vector.

Therefore if the regression of two or more series which are individually integrated yield residuals with lower order of integration; they are said to be cointegrated. There is the special case of cointegration in which the linear combination of series integrated of the same order is stationary. Most of the cointegration tests are based on this special case in which series integrated of order one yields a linear combination which is stationary. The informal induction of cointegration is that if two or more series are moving together over time then the extent by which they divert from each other will have a stationary characteristic.

Cointegration analysis generally involves four steps:

i) Ensuring that the individual elements of y_t are I(1) processes;

ii) Determining the order of the vector autoregression (VAR) model;

iii) Performing cointegration tests to determine the rank of the cointegrated system; and

iv) Estimating the error-correction model.

3.4.1.1 Stationarity Test

A series is said to be stationary if the moments of the series (mean, variance etc) are independent of time and are integrated of order zero. Nonstationary series have infinite variance asymptotically and therefore any inference made will be invalid due to both spurious and inconsistent regression problem.

The study used the Augmented Dickey-Fuller (ADF) unit root test to examine if the elements of Xt are I(1) processes individually. Since the ADF test depends critically on the assumption about the underlying process and the estimated regression, we conducted the test based on three variations of the Dickey-Fuller designed to take account of the role of the constant term and the trend.

The test is generally based on the AR(1) process $X_t = pX_{t-1} + v_t$ and is stationary when $|p| < 1$, but, when p = 1; it becomes the nonstationary random walk process $X_t = X_{t-1} + v_t$. Hence, to test for stationarity is basically to examine the value of p. In other words, we test whether p is equal to one or significantly less than one- **the unit root tests.**

To formalize this procedure a little more, we consider the AR(1) model:

$$X_t = pX_{t-1} + v_t \text{..............................} (*)$$

Where v_t are independent random errors with zero mean and constant variance σ_v^2, i.e. white noise. We then test for nonstationary by testing the null hypothesis that p = 1 against the alternative hypothesis that $p < 1$. This one-sided (left tail) test is put into a more convenient form by subtracting X_{t-1} from both sides of (*) to obtain

$$X_t - X_{t-1} = pX_{t-1} - X_{t-1} + v_t$$

$$\Delta X_t = (p-1)X_{t-1} + v_t$$

$$= \gamma X_{t-1} + v_t$$

Where $\gamma = p - 1$ and $\Delta X_t = X_t - X_{t-1}$; then the hypotheses can be written in terms of either p or γ as:

$$H_0 : p = 1 \longleftrightarrow H_0 : \gamma = 0$$

$$H_1 : P < 1 \longleftrightarrow H_1 : \gamma < 0$$

In particular, we estimate the following three ADF models:

i) A random walk (no trend and no constant-drift)

$$\Delta X_t = \lambda X_{t-1} + \varepsilon_t \tag{3.4}$$

ii) ADF with intercept but no trend

$$\Delta X_t = \alpha_t + \lambda X_{t-1} + \varepsilon_t \tag{3.5}$$

iii) ADF with intercept and trend

$$\Delta X_t = \alpha_t + \delta_t + \lambda X_{t-1} + \varepsilon_t \tag{3.6}$$

Obviously, the three equations differ from one another in the assumption about whether an intercept, or a deterministic time trend, is included in the regression.

Generally, we test the following null hypothesis that corresponds to the above regressions:

H_0*: non stationary (unit root)*

H_a*: stationary*

3.4.1.2 Lag Length Selection

For purposes of determining the order of the cointegration test and the error correction model, Akaike information criterion (AIC) and the Bayesian information criterion (BIC) derived by Schwarz (1978) are normally used. BIC is known to be more parsimonious than AIC given that it usually selects a model with a lower order as the optimal model than the one chosen by AIC.

According to Stock and Watson (2007), choosing the order p of an autoregression requires balancing the marginal benefit of including more lags against the marginal cost of additional estimation uncertainty. On the one hand, if the order of an estimated autoregression is too low, you will omit potentially valuable information contained in the more distant lagged values. On the other hand, if it is too high, you will be estimating more coefficients than necessary, which in turn introduces additional estimation error into your forecasts. Various statistical methods can be used, but two most important ones are BIC and AIC.[1] The two criterions are derived as follows:

The Schwarz Information Criterion estimates p by minimizing an 'information criterion'.

$$BIC(p) = ln\frac{RSS(P)}{T} + (P+1)\frac{lnT}{T} \tag{3.7}$$

[1] Others including FPE, HQ, and LR are also used in empirical studies.

Where RSS(p) is the sum of squared residuals of the estimated AR(p). The BIC estimator of p, $\hat{p}$, is the value that minimizes BIC(p) among the possible choices p = 0,1, , p_{max}, where p_{max} is the largest value of p considered.

Because the regression coefficients are estimated by OLS, the sum of squared residuals necessarily decrease (or at least does not increase) when you add a lag. In contrast, the second term is the number of estimated regression coefficients (the number of lags, p, plus one for the intercept) times the factor (lnT)/T. This second term increases when you add a lag. The BIC trades off these two forces so that the number of lags that minimizes the SIC is a consistent estimator of the true lag length.

The Akaike Information Criterion on the other hand estimates p as;

$$AIC(p) = ln\frac{RSS(P)}{T} + (P+1)\frac{2}{T} \tag{3.8}$$

In view of our limited data, the optimal lag for both cointegration test and the error correction model was selected using BIC.

3.4.1.3 Johansens Methodology

Johansen test for cointegration was used to test the existence of long run relation between the variables. The rejection of null hypothesis indicates that the series are cointegrated.

H_0: *the series are not cointegrated*
H_a: *the series are cointegrated*

Johansens trace and maximum eigenvalue statistics are used to determine the number of cointegrating equations based on Johansens maximum likelihood (ML) estimator.

The hypothesis of interest involves the rank of γ. If the rank of γ is q and $q \leq n-1$, then one can decompose γ into two n x q matrices α and β such that $\gamma = \alpha\beta'$. The matrix β contains q linear cointegration parameter vectors whereas α is a matrix consisting of n error-correction parameter vectors. The maximum likelihood estimate of α is obtained using the OLS regression of Δy_t on Δy_{t-1},..., Δy_{t-p+1} and 1 whose residual is ε_{0t}. Similarly, the maximum likelihood estimate of β can be obtained from the OLS regression of y_{t-1} on Δy_{t-1},...,Δy_{t-p+1}, and 1 whose residual is ε_{lt}. Based on the residuals ε_{0t} and ε_{1t}, we have the residual product matrices.

$$S_{ij} = T^{-1} + \sum_{t=1}^{T} \varepsilon_{it}^{'} \varepsilon_{jt} \qquad 1, j = 0, 1 \tag{3.9}$$

We then solve the eigenvalue system

$$|\lambda S_{11} - S_{10} S_{00} S_{01}| = 0$$

for eigenvalues $\lambda_1 > \cdots > \lambda n$ and eigenvectors $\psi = (\psi_1, \cdots, \psi_n)$. The estimates for α and β are given by $\acute{\alpha} = S_{01}\beta$ and $\beta = (\psi_1, \cdots, \psi_q)$,where $\psi_1, \cdots, \psi_q$ are the eigen-vectors associated with the q largest eigenvalues. Two Johansen's maximum likelihood tests; the maximal eigenvalue test and the trace test, can then be used to determine the number of cointegration vectors. The statistic from the maximal eigenvalue test for the null hypothesis of q cointegration vectors against the alternative of $q+1$ cointegration vector is

$$\lambda_{max} = -Tln(1 - \lambda_{q+1});$$

and the trace test statistic for the null hypothesis of at most q cointegration vectors is

$$\lambda_{trace} = \sum_{j=q+1}^{n} ln(1 - \lambda_j)$$

We then check for consistency with the hypothesis of at least one cointegration vector. Where this is the case, we go ahead and use the maximum likelihood method to test the hypotheses regarding the restriction on β.

3.4.1.4 Estimation of the Error Correction Model

Subsequently, with the number of cointegration vectors determined through the maximal eigen-value and trace tests, we continue to estimate the error-correction model of the lapse rate, stock market index, inflation rate, GDP growth rate and unemployment rate.

$$\Delta y_t = \mu + \gamma y_{t-1} + \xi_1 \Delta y_{t-1} + \cdots + \xi_p \Delta y_{t-p-1} + \varepsilon_t \tag{3.10}$$

where the vector y_t consists of the lapse rate, stock market index, inflation rate, GDP growth and unemployment rate at time t, Δ is the first-order difference operator, p is a 5 x 1 intercept vector, γ is a 5 x 5 constant matrix, t is a 5 x 1 white noise error term vector, and the optimal lag p is determined according to the Bayesian Information Criterion.

Appendix 3(a) shows the time series for the lapse rate, stock market index, inflation rate, GDP growth and unemployment rate from 1964 through 2013. It is apparent that there is a time trend in these five series, although there is a serious inflationary setback in 1993 and some good performance in the stock market during the later period between 2006 and 2008. Based on this observation, the general principle would guide us to perform the ADF test based on regression (3.6).

We also conduct the ADF test on the first-order differences of the series to confirm that all of these series are I(1) processes rather than processes with higher-order integration, that is, I(j), $j > 1$. If this is the case, the ADF test would reject the null hypothesis of a unit root in these differenced series at conventional significance levels. Since the first-order differences of these series, as shown in appendix 3(b), fluctuate randomly around zero, we should include neither an intercept nor a deterministic time trend in the regression of the ADF test. In other words, we choose the form of regression (3.4) for the first-order differences of the series.

3.5 Diagnostic Test

3.5.1 Multicolinearity Test

This test was carried out to establish the independence and or relationship of all the variables. Various methods for testing multicolinearity exist, for this study, the correlation matrix was used.

In testing linear relationship between the explanatory variables; correlation matrix helps in determining the strengths of variables in the model. It enables the researcher to know which variable to drop from the equation. A correlation statistics greater than 0.8 reflects a high correlation among variables.

3.5.2 Normality, Heteroscedasticity and Serial Correlation Tests

The study also used Breusch-Pagan-Godfrey, Jarque-Bera statistic, Breusch-Godfrey LM Test, and cumulative sum test in testing for heteroscedasticity, normality, serial correlation and stability respectively. This was done to ensure that the coefficients of the estimate are efficient, consistent and reliable in making inference.

3.5.3 Impulse Response Test

An impulse response function is a shock to a restricted or unrestricted VAR. A unit shock is applied, to each variable, to see the effect on the dependent variable. For calculating impulse response, the ordering of the variable is important. This study used Cholesky of adjusted method in setting the ordering of the variables.

A positive shock of one standard deviation was applied to the innovation (error term) to see the reaction of the dependent variable. It should be noted that the shock is applied to each variable to see the reaction of all the variables but in this study we are interested in the reaction of the lapse rate to the other variables.

3.5.4 Variance Decomposition

Variance decomposition enables us to forecast ahead. For this analysis three years and below will be considered as short run while the rest will be considered long run and therefore three and ten years will be used to indicate short run and long run forecasts respectively.

Chapter 4

DATA ANALYSIS AND RESULTS

The model outlined in chapter three is estimated and the results reported in this chapter.

4.1 Introduction

Our sample contains the annual voluntary termination rates for all ordinary life insurance policies in force from 1964 to 2013. Data on lapse rate and stock market index were acquired from the Statistical Abstracts (various issues), an annual statistical report of the Kenya National Bureau of Statistics (KNBS). The data in the Statistical Abstract are derived from the annual statements filed by life insurance companies with the Insurance Regulatory Authority, IRA's surveys, Nairobi Securities exchange and/or external sources such as government agencies and trade associations. The voluntary termination rate equals the ratio of the number of lapsed or surrendered policies to the mean number of policies in force. Compared to the other studies that have been done before, our sample spans a longer period and extends over the era of highly volatile interest rates in the 1980s and early 1990s. We obtained the inflation, unemployment and GDP growth rates from the World Bank Development reports and the same were compared with the various issues done by the Central Bank of Kenya.

4.2 Empirical Findings and Interpretations

4.2.1 Stationarity Test

As a preliminary analysis, each time series variable is subjected to ADF test to test for stationarity. If variables are not stationary in levels, appropriate differencing is required until the variables become stationary. We employ the ADF test to examine whether there are unit roots in these four variables. As mentioned before, the asymptotic distribution of the unit root test depends on whether the selected optimal regression includes an intercept, a deterministic time trend, or none of them. We thus need to decide which specification to use for the ADF test. Specifically, we follow the general principle suggested by Hamilton (1994) to fit a specification that is a plausible description of the data under both the null and the alternative hypothesis. The results for unit root tests in both levels and at first differences are presented in table (4.1) below.

Table 4.1: **ADF Radom Walk (no trend, no drift)**

Variable	Level	1st Difference	Critical Value(5 %)	Decision
Lapse Rate	-2. 715080		-1.947665	I(0)
Stock Market Index	0.268430	-6.121008		I(1)
Inflation Rate	-2.012471			I(0)
GDP Growth	-0.999722	-7.527738		I(1)
Unemployment Rate	-0.155363	-2.601071		I(1)

The H_0 is rejected when the ADF statistic >5% critical value. The results indicate that the variables are integrated of order one, I(1) except lapse rate and inflation which are integrated of order zero. I(0).

The two variables are therefore stationary in levels at the 5% level of significance. After the first differencing, the stock market index, GDP growth and unemployment rate became stationary at the 5% level of significance.

The results after first differencing indicated that all the variables were stationary thus appropriate to estimate the long-run lapse behavior.

The data in this study is time series, thus it was important to run unit root test to avoid spurious results associated with non-stationary variables. It is critical to ensure that the model is in a stable equilibrium. Stationarity tests were, therefore, done to establish whether the data is stationary or not and also to determine the order of integration of the variables. The objective is to ensure that the variables are not of order 1(2) to avoid spurious results.

4.2.2 Lag Length Selection

The optimal maximum lag length was tested sequentially, using the five information criteria reported in Eviews; the Sequential Likelihood Ratio (LR), the Final Predictor Error (FPE), Akaike Information Criterion (AIC), Bayesian Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ).

Table 4.2: **Optimal Lag Length Selection**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-951.1192	NA	3.22e+11	40.68592	40.88275	40.75999
1	-881.5420	121.3899	4.86e+10	38.78902	39.96997*	39.23342*
2	-853.0043	43.71737*	4.34e+10*	38.63848*	40.80355	39.45321

* indicates lag order selected by the criterion

Table 4.2 shows that the test for optimal lag length 1 is identified. The Schwarz information criterion (SC) suggests that the maximum lag length is 1 for each variable. The existence of a long run relationship between lapse rate and the other variables is therefore assessed using 1 lag. The Johansen Maximum likelihood was used to test for the presence of a co-integrating relationship.

4.2.3 Johansen Cointegration Test

Johansen technique is a multivariate autoregressive model. It is an enhancement over the single equation estimation technique since it allows the possibility of dealing with more than one cointegrating vector. It is also able to separate the long-run equilibrium relationships from the short-run dynamics.

This approach uses the likelihood (LR) tests based on Trace and Maximum Eigenvalue statistics. For this statistics, the null hypothesis is that there are r or fewer cointegration vectors and 1+r cointegration vectors, respectively.

Table 4.3 in the next page shows the eigenvalues and trace statistics results.

Table 4.3: **Johansen Cointegration Test**

Unrestricted Cointegration Rank Test (Trace and Max)

Hypothesized No.of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Max-Eigen Statistic	0.05 Critical Value
None*	0.641229	93.78614	69.81889	48.17832	33.87687
At most 1	0.350111	45.60781	47.85613	20.25486	27.58434
At most 2	0.247337	25.35296	29.79707	13.35450	21.13162
At most 3	0.207840	11.99846	15.49471	10.95061	14.26460
At most 4	0.022048	1.047852	3.841466	1.047852	3.841466

Trace and max test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level

The results show the existence of at least one cointegrating equations at 5% level of significance. To accept the null hypothesis, H_0, the Trace and Maximum Eigen value statistics must be smaller than the 5 percent critical values reported for each. The results indicate that both the Trace and Maximum Eigenvalue tests reject zero in favour of at least one cointegration equation. This result proves that the variables are tied together in a single way in the long run, that is, there is one unique long-run equilibrium relationship and therefore the suitable estimation technique is ECM.

4.2.4 Error Correction Model (ECM)

Given the evidence that the variables in the specified lapse rate model has a long run relationship as shown by the Johansen cointegration technique, our next step is to estimate how the lapses respond, in the long run, to changes in its determinants. The long run regression equation was normalized on lapse rate and the estimated long-run function is thus as follows:

Table 4.4: **Error Correction Estimates**

Sample (adjusted): 1967 2013 observations =41

	Coefficient	Std. Error	t-Statistic	Prob.
D(LR)				
ECM	-0.442821	0.091123	-4.859590	0.0000
D(LR(-1))	0.032319	0.129982	0.248645	0.8049
D(SMI(-1))	-0.004926	0.001477	-3.334550	0.0019
D(UR(-1))	-0.231817	0.131114	-1.768057	0.0847
D(INF(-1))	0.014488	0.076980	0.188203	0.8517
D(GDP(-1))	-0.371563	0.123486	-3.008957	0.0045
C	0.286669	0.555372	0.516174	0.6086

R-squared	0.475888	Mean dependent var	0.017660
Adjusted R-squared	0.397271	S.D. dependent var	4.849824
S.E. of regression	3.765191	Akaike info criterion	5.626079
Sum squared resid	567.0666	Schwarz criterion	5.901632
Log likelihood	-125.2128	Hannan-Quinn criter.	5.729771
F-statistic	6.053256	Durbin-Watson stat	1.782648
Prob(F-statistic)	0.000142		

ECM model is a single equation model.

4.2.4.1 Long run effect(adjustment)

The ECM coefficient is negative and significant (probability value $< 5\%$) and therefore, all the explanatory variables affect Lapse rate and the deviation from the long run equilibrium is adjusted for. $\eta = -0.442821$ implies the speed of adjustment towards long run equilibrium at a rate of 44.28%.

4.2.4.2 Short run Dynamics

For the explanatory variables, although the lapse rate and inflation rates coefficients are positive thus conforming to expectations but they are not statistically significant. Both unemployment and stock market index coefficients are negative and they do not conform to expectation. GDP growth coefficient on the other hand is negative and conforms to expectation.

$\beta_1 = 0.032319 > 0$ and therefore conforms to the expectations. β_1 is statistically insignificant (probability value $> 5\%$) implying that there is no short run effect from previous years lapsed rate to the current lapse rate.

$\beta_2 = -0.004926 < 0$ and therefore does not conform to the expectations. β_2 is statistically significant (probability value $< 5\%$) implying the existence of short run effect from stock market index to lapse rate. This means that if the stock market index increases by 1% lapse rate decrease by 0.004926% in the short run.

$\beta_3 = -0.231817 < 0$ and therefore does not conform to expectations. β_3 is not statistically significant (probability value $> 5\%$) and therefore there is no short run effect from unemployment rate to lapse rate.

$\beta_4 = 0.014488 > 0$ and therefore conforms to expectations. β_4 is statistically insignificant (probability value $> 5\%$) and therefore inflation cannot cause policy lapse in the short run.

$\beta_5 = -0.371563 < 0$ and therefore conforms to expectations. β_5 is statistically significant (probability value $< 5\%$) and therefore GDP growth has an influence on lapsation in the short run. This means that if GDP growth increases by 1%, lapse rate decrease by 0.371563% in the short run.

The R^2

$R^2 = 0.475888$ meaning that the explanatory variables in the model explain 47.6%

of the variations in lapse rate over the study period and that 52.4% is explained by other factors not included in the model. Policy lapses are caused by many factors, as discussed in chapter 1, section 1.1.3; and this explains the high percentage of the factors excluded in the model. Since the F statistic is significant, as shown below, the model is acceptable.

The F Statistic

The F-statistic of 6.053256 and its probability value of 0.000142 ($< 5\%$) show that the overall model is statistically significant at 5% levels of significance. This is because it is greater than the critical value of 2.57 and 3.79 at 1% and 5% respectively. This means that all the explanatory variables jointly explain policy lapses.

4.3 Diagnostic Tests and Results

4.3.1 Multicolinearity Test

The results of this test are presented in table 4.5 below.

Table 4.5: **Correlation Matrix**

	Lapse Rate	SMI	UE	inflation	gdp
Lapse Rate	1.0000				
SMI	0.1699	1.0000			
UE	0.0463	0.2461	1.0000		
Inflation	-0.155	0.0936	0.0130	1.0000	
gdp	0.0405	-0.1278	0.0778	-0.3184	1.0000

The correlation matrix results show that the variables in this study; lapse rate, stock market index, inflation rate, GDP growth and unemployment rate are not strongly correlated. Therefore, the study did not drop any of the variables in the study.

4.3.2 Normality, Heteroscedasticity, Serial Correlation Test and Stability

The results for these tests are presented in table 4.6

Table 4.6: **Diagnostic Test Statistics**

	TEST	H0	Obs*R-Squared	Prob chi2
Serial correlation	Lm test	No autocorrelation	4.603515	0.1001
Normality	Jarque-bera test	Residuals normally distributed	5.112400	0.077599
Heteroscedasticity	Breusch-Pagan-Godfrey	Homoscedastic	13.55603	0.1942
Stability	CUSUM	Stable		

The null hypothesis (H_0) is rejected if the probability value χ^2 is less than 5%.

Since the probability values, χ^2 are all greater than 5%, we fail to reject any of the null hypotheses for serial correlation, normality and heteroscedasticity.

The results from the diagnostic tests therefore indicate that the model has no serial correlation, the residuals are normally distributed and homoscedastic. The cumulative sum test shows that the parameters are stable (see section 4.3.3 below-the curve is within the two red lines). Since the model has the characteristics of a good regression; the coefficients are efficient, consistent and reliable in making the inference.

4.3.3 Structural (Recursive) Stability Test

The stability test determines whether a statistically significant structural break-point can be identified over the estimation period. This impact might be due to some financial sector developments or policy changes that occurred at a particular time period. The stability of the lapse rate is of great importance because during the study, the economy experienced many changes in the financial sector.

This study employed the CUSUM to test for structural changes on the lapse behaviour although the long-run relationship may have been confirmed through the cointegration test. It is possible that some changes in the Kenyan economy may have rendered unpredictable short-run deviations of lapse rate from the long-run equilibrium values. The CUSUM test is very important in detecting systematic changes in the regression coefficient. The test (Brown et al., 1975) is based on the cumulative sum of the recursive residuals. This option plots the cumulative sum together with the 5% critical lines. The test finds parameter instability if the sum goes outside the area between the two critical lines (Greene, 2003).

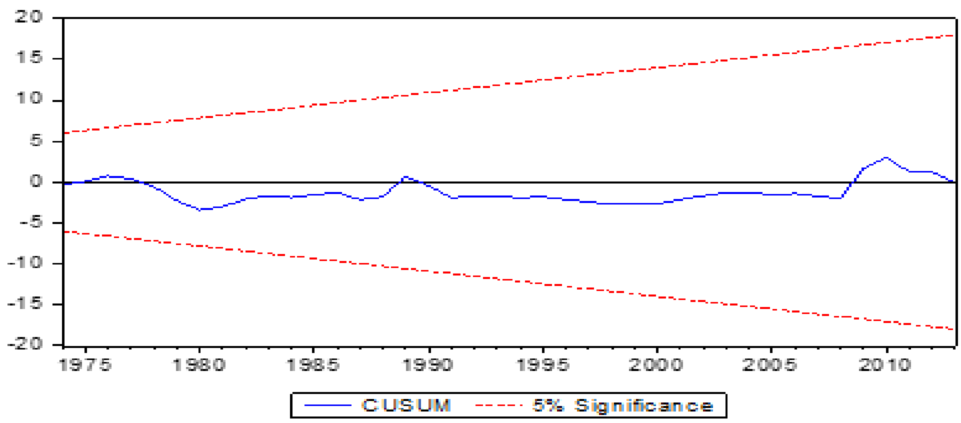

Figure 4.1: **Stability Condition**

The recursive estimations reported in fig 4.1 above generally shows stable lapse behaviour for the period under review. Lapse rate lies within the 5% critical bounds (dotted lines) for the CUSUM test, within the study period.

4.3.4 Impulse Response

Impulse response functions show how innovations of given endogenous variables stretch through each and every given endogenous variable and eventually how it affects the original variable itself. These indicate how each endogenous variable responds overtime to innovations or shocks to each of the endogenous variables in the model.

Table 4.7, represents the impulse response functions.

Table 4.7: **Response of LR**

PERIOD	LR	SMI	UR	INF	GDP
1	3.765191	0.000000	0.000000	0.000000	0.000000
2	2.210391	-1.458604	-0.209921	1.108792	1.447536
3	1.527417	-0.265955	-0.075085	0.776381	2.633448
4	1.734383	0.495138	-0.472583	0.978214	2.391851
5	1.938017	0.067284	-0.276234	1.097265	2.038160
6	1.804818	-0.081482	-0.274238	1.044888	2.265654
7	1.770971	0.085788	-0.311034	1.013664	2.295767
8	1.816735	0.097917	-0.306971	1.038479	2.239125
9	1.817565	0.048069	-0.300904	1.043109	2.235366
10	1.804925	0.051749	-0.299259	1.034857	2.252876

We are observing the responsiveness of the dependent variables in the ECM when a positive shock of one standard deviation is put to the error term. A period of ten years was selected to assess how far into the future the dependent variable reacts to the other variable. The explanations below are deduced from table 4.8 above together with the graphs on impulse response functions- appendix 5.

Response of lapse rate to lapse rate (reacting to its own); when a positive shock of one standard deviation is given to lapses rate, lapse rate remains positive. The lapse rate will initially go down but start to increase after three years before becoming steady after six years until year ten. There is therefore a positive association between lapse rate and itself.

Response of lapse rate to stock market index; if a positive shock of one standard deviation is given to stock market index; lapse rate will be negative before becoming positive after three years and eventually becomes zero after five years.

Response of lapse rate to unemployment; a positive shock of one standard deviation given to unemployment rate will have a negative impact on lapse rate since lapse rate remains negative.

Response of lapse rate to inflation; a positive shock of one standard deviation to inflation leads to a positive effect on lapse rate which first increases then decreases after two years before gradually becoming steady after three years.

Response of lapse rate to GDP; when a positive shock of one standard deviation is given to GDP, lapse rate remains positive. The rate first increases but after two years; it decrease before becoming steady after five years.

4.3.5 Variance Decomposition

Table 4.8 in the next page shows the variance decomposition for the variables under study.

Table 4.8: **Variance Decomposition of Lapse Rate (LR)**

Period	S.E.	LR	SMI	UR	INF	GDP
1	3.765191	100.0000	0.000000	0.000000	0.000000	0.000000
2	4.955690	77.61960	8.662960	0.179433	5.006009	8.531995
3	5.874185	62.00505	6.370640	0.144046	5.309755	26.17051
4	6.682850	54.64244	5.471095	0.611366	6.245093	33.03001
5	7.338618	52.28730	4.545410	0.648671	7.414456	35.10416
6	7.963636	49.53816	3.870393	0.669432	8.017831	37.90418
7	8.541546	47.36039	3.374466	0.714511	8.377947	40.17268
8	9.080444	45.90864	2.997450	0.746502	8.720960	41.62645
9	9.588316	44.76740	2.690836	0.768001	9.005085	42.76868
10	10.07135	43.78790	2.441553	0.784390	9.217811	43.76834

Shock to Lapse Rate (own shock); in the short run, an impulse to LR accounts for 62% variation of the fluctuation in LR while in the long run, the same contributes 43.8% of fluctuation in LR indicating that in the long run, contribution to LR has gone down and therefore a shock to LR cannot contribute much to fluctuations in LR.

Shock to stock market index; an innovation to stock market index can cause 6.4% fluctuations in LR in the short run while in the long run it can contribute 2.4% of fluctuation in the variance of LR implying that a shock in SMi cannot contribute to LR much.

Shock to unemployment rate; impulse to unemployment rate accounts for 0.1% in the variation of the fluctuations in LR, in the short run, but contribute 0.8% in the variance forecast error of LR implying that a shock to unemployment rate cannot contribute much to the fluctuation of LR neither in the short run nor in the long run.

Shock to inflation; in the short run, inflation contributes 5.3%. It however contributes 9.2% of the fluctuations in lapse rate in the long run. This implies that inflation has an impact in lapse rate.

Shock to GDP; of the variance fluctuations in lapse rate, innovation to GDP causes 26.2% in the short run and 43.8% in the long run implying therefore that GDP really causes fluctuations in lapse rate.

Chapter 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

The overall objective of this study was to construct a robust lapse rate model that accurately specifies the lapse behaviour and one that helps the insurers track their lapse data, especially involving the sensitivity of the lapse rate to the changes in specific economic variables; the stock exchange share index, economic growth, unemployment rate and the overall inflation levels.

The present study is important because it contributes to the debate on various hypotheses that have been put forward in an attempt to establish the precise determinants of the lapse behaviour. The study also undertook to test whether causality existed between lapse rate and the specified variables using time series annual data between 1964 and 2013.

To meet the objective of the study, data on various macroeconomic variables were collected, for the period under consideration, from various sources that included the Statistical abstracts, economic surveys, Nairobi Securities Exchange, CBK publications and other sources including the World Bank.

The first objective of the study was to develop a model that accurately specifies the lapse behaviour and to determine the impact of the various economic variables on lapse rates. Since it was not possible to directly estimate the impact using ordinary least squares technique (OLS), it prompted the use of Cointegration techniques because of the need to separate the potential long-term relationship among lapse rate, stock market performance, economic growth, inflation and unemployment rate from their short-term adjustment mechanisms.

The second objective was to re-examine the contending lapse rate hypotheses: the emergency fund hypothesis and the interest rate hypothesis. The ECM analysis revealed a long run causality running from all the explanatory variables to the dependent variable. The findings also indicate that stock market index and GDP affect lapse rate in the short run.

We further performed an impulse response analysis to examine the economic significance of the GDP growth and stock market index on the lapse rate. We found that the lapse rate responds far more strongly to the random shock from the GDP growth than to the shock from the stock market index. In other words, the GDP growth has a more significant economic impact upon the lapse rate than the stock market index. We therefore conclude that the emergency fund hypothesis dominates the interest rate hypothesis in interpreting the dynamics of the lapse rate.

5.2 Conclusion

Understanding the determinants of the lapse rate is important because policy lapse can have negative impacts on the insurer's profitability and liquidity. Furthermore, policy lapse could cause the cash flow of the insurance policies to be sensitive to the share index and significantly change the duration, convexity, and value of the insurance policy. Despite the importance of policy lapses, most insurers do not have a reliable model to specify lapse behaviour, especially involving the sensitivity of the lapse rate to the share index. Insurers have done little to help them track their lapse data in a manner that allows them to accurately model the lapse rate and by extension, enable them manage the lapse risk.

This article extends the literature by using a more comprehensive method and a longer data period and while the previous studies focused exclusively on the short-term dynamics, this study investigated both the short and long-term lapse behaviour using the cointegration model developed by Engle and Granger (1987). Our sample period covered 50 years and captured the important era of economic liberalization, a phenomenon that other studies either missed out or had shorter sampling periods.

We find that the influence of GDP growth and stock market index, upon the lapse rate in the short-run, is statistically significant whereas the short-term impact of the stock market index is only marginally significant. This evidence seems consistent with the emergency fund hypothesis as well as with the findings of Outreville (1990). In addition, we discover a long-term relationship among the lapse rate, stock market index, inflation rate, GDP growth and unemployment rate, which is not identified in Outreville's paper. Both the GDP growth and the stock market index have statistically significant power in explaining long-term behaviour of the lapse rate.

A shock of one standard deviation on GDP in this case ensures that lapse rate remains positive. It increases but starts to decrease after two years before becoming steady after five years as seen in the impulse response functions. Variance decompositions also lend more credence to GDP innovations, both in the short run and in the long run. The study found that overall, GDP growth play crucial role in influencing the lapse behaviour in the industry. This result gives weight to the proponents of the emergency fund hypothesis.

We speculate that the long-term causality from the GDP growth and stock market index on the lapse rate could occur through two mechanisms. The first mechanism suggested by Engle and Granger (1987) assumes that there is a long-term equilibrium relationship among the lapse rate, GDP growth and stock market index and any equilibrium error will be corrected gradually. The causality from the GDP growth and stock market index on the lapse rate reflects the partial adjustment of a temporary disequilibrium economy system. On the other hand, Campbell and Shiller (1988) suggested an alternative mechanism, arguing that causality resulted from the optimal decision making process of policyholders in the sense of rational expectation.

5.3 Limitations and Areas for Further Research

We are aware that the changed mix of various types of policies over the last several decades might have some impact on the lapse rate and the relationship that exists among the lapse rate, stock market rate, inflation rate, GDP growth and the unemployment rate. However, we dont have adequate data to assess such an impact. This is a limitation of our study which creates a need for further research for inclusion of other explanatory variables in the analysis.

A promising future research topic is to establish such a model. Another path for future work could be to explicitly compare the forecasting performance of our error correction model with exogenous I(1) variables with that of Outrevilles model. An interesting research topic is applying our empirical model to quantify the reserve risk of policy issuers with respect to variations in the stock market index.

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APPENDICES

Appendix 1: Risk Map

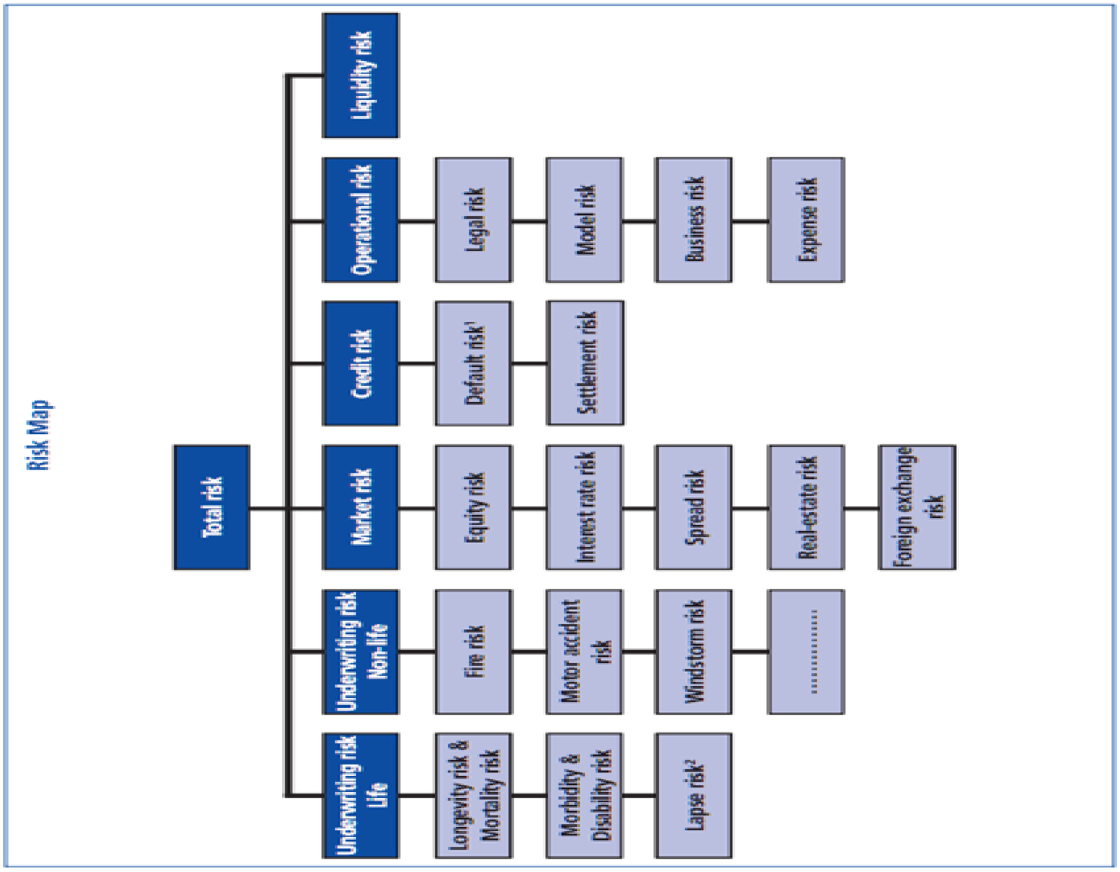

Figure 5.1: **Risk Map**

The tree structure provides a clear example of which variables fall into which risk category.

Key:

LR = Lapse Rate, computed as,

LR = ((policies issued and discontinued)/(avg no.of policies in force*))x 100

* mean of the total life policies at the start and end of year

GDP = Gross Domestic Product

INF = Inflation Rate

UE = Unemployment Rate

SMI = Stock Market Index**

** Annual average of the monthly stock market indices

Note : *These, together with the formulae herein, explain the process followed to derive the lapse rate tabled in appendix 2 overleaf.*

Figure 5.2: **Appendix 2: Raw Data**

YEAR	LR	GDP	INF	UE	SMI
1964	1.74	4.9644673	-0.0993049	10.5	0
1965	2.09	2.0090942	3.5785288	9.8	8
1966	2.41	14.728566	5.0143954	2.9	100
1967	9.03	3.3612321	1.7591958	11.1	63
1968	6	7.98269	0.3667116	7.1	60
1969	4.18	7.9592245	-0.171501	20.5	69
1970	4.88	-4.6554469	2.188527	5.2	90
1971	6.36	22.173892	3.7802061	12.5	127
1972	2.41	17.082429	5.8316447	9.2	147
1973	11.11	5.8965802	9.2811942	2.9	138
1974	6.7	4.0656173	17.809948	4.6	114
1975	2.95	0.8822032	19.120184	10.7	76
1976	3.13	2.1539645	11.44903	8.6	97
1977	4.52	9.4537978	14.820964	15.2	188
1978	3.78	6.9124936	16.931782	11.6	316
1979	2.53	7.615226	7.9793526	1.9	256
1980	1.95	5.5919762	13.858181	2.8	256
1981	2.96	3.7735442	11.603053	1.7	256
1982	5.87	1.5064783	20.666715	4.6	241
1983	3.52	1.3090502	11.397783	5.4	225
1984	2.88	1.755217	10.284098	4.2	181
1985	2.58	4.3005618	13.006566	3.2	254
1986	3.55	7.1775554	2.534276	2.3	348
1987	0.96	5.9371074	8.6376732	7.7	313
1988	2.75	6.2031838	12.264963	6.7	321

YEAR	LR	GDP	INF	UE	SMI
1989	12.53	4.6903488	13.789317	9.8	441
1990	2.89	4.192051	17.781814	9.4	347
1991	1.5	1.4383468	20.084496	10.1	542
1992	2.31	-0.799494	27.332364	10.1	670
1993	2.36	0.3531973	45.978881	10.1	983
1994	2.8	2.6327845	28.814389	10	2630
1995	4.85	4.4062165	1.5543282	9.9	2258
1996	3.03	4.1468393	8.8640874	9.9	2033
1997	2.76	0.4749019	11.361845	9.9	2202
1998	1.72	3.2902137	6.7224365	9.8	1933
1999	1.51	2.3053886	5.7420011	9.8	1704
2000	1.52	0.5996954	9.9800252	9.8	1317
2001	2.77	3.7799065	5.7385981	9.8	1012
2002	3.34	0.5468595	1.9613082	9.7	695
2003	3.16	2.9324755	9.8156906	9.6	1323
2004	1.84	5.1042998	11.624036	9.6	1819
2005	1.86	5.9066661	10.312778	9.5	2401
2006	3.79	6.3306328	14.453734	9.5	3045
2007	3.82	6.9932852	9.7588802	9.5	3500
2008	4.89	1.5269488	26.239817	9.4	2994
2009	22.76	2.7352862	9.2341259	9.4	1971
2010	22.76	5.7648271	3.9613889	9.3	2813
2011	5.43	4.3759336	14.02155	9.3	2467
2012	8.62	4.5980461	9.3783959	9.4	2456
2013	3.24	5.74	5.7182741	9.4	3173

Figure 5.3: **Appendix 2: Raw Data**

Sources: Republic of Kenya Statistical Abstracts and Economic Survey, various issues. Nairobi. World Bank and International Financial Statistics. Washington, DC.

Appendix 3(a):Time Series at Level

Time Series of Lapse Rate, Stock Market Index, GDP, inflation and Unemployment (1964-2013)

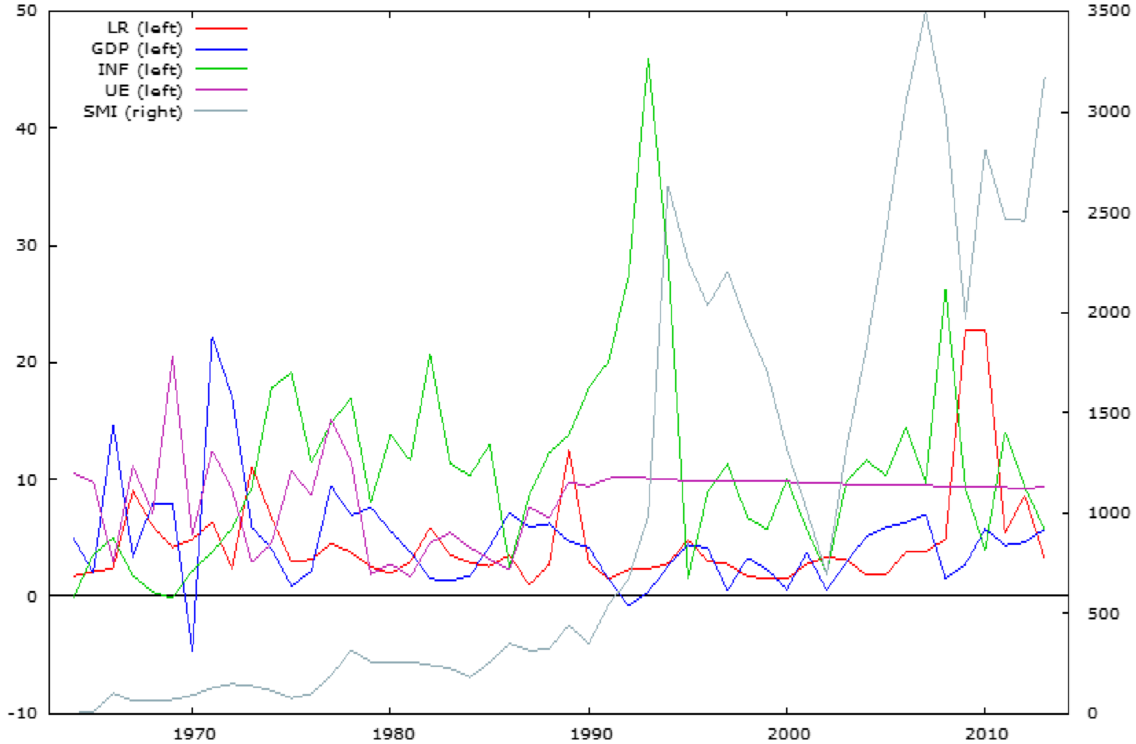

Figure 5.4: **Time Series at Level**

Appendix 3(b): 1^{st} Order Differenced Times Series

Time Series of 1st

order differenced Lapse Rate, SMI, GDP, inflation and Unemployment (1965-2013)

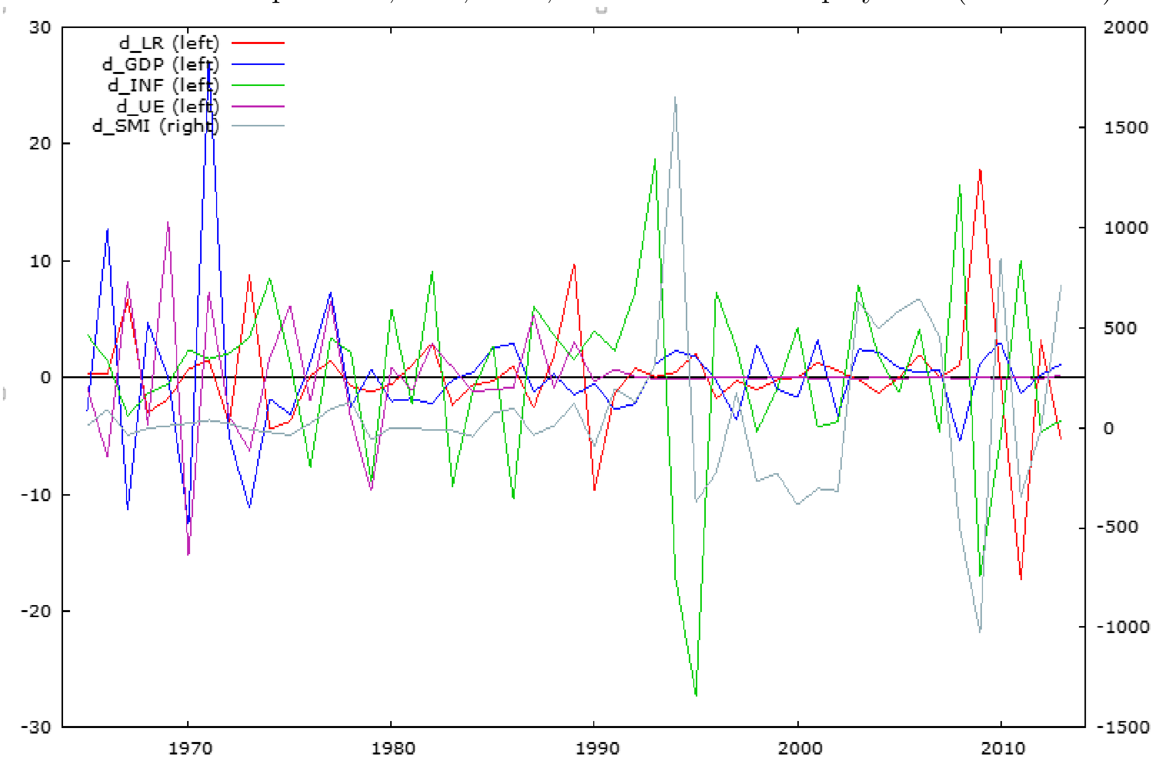

Figure 5.5: 1^{st} **Order Differenced Times Series**

Appendix 4: Unit Roots

Table 5.1: **WITH CONSTANT**

Null Hypothesis: LR has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.314150	0.0012
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

Table 5.2: **WITH TREND AND CONSTANT**

Null Hypothesis: LR has a unit root

Exogenous: Constant, Linear Trend

Lag Length: 0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.318565	0.0065
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

Table 5.3: **WITH CONSTANT (LEVEL)**

Null Hypothesis: LR has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.706102	0.8354
Test critical values:	1% level	-3.574446	
	5% level	-2.923780	
	10% level	-2.599925	

Table 5.4: **WITH TREND AND CONSTANT (LEVEL)**

Null Hypothesis: SMI has a unit root

Exogenous: Constant, Linear Trend

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.617017	0.2749
Test critical values:	1% level	-4.161144	
	5% level	-3.506374	
	10% level	-3.183002	

Table 5.5: **WITH CONSTANT (1st DIFFERENCE)**

Null Hypothesis: D(SMI) has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.208921	0.0000
Test critical values:	1% level	-3.577723	
	5% level	-2.925169	
	10% level	-2.600658	

Table 5.6: **WITH TREND AND CONSTANT (1st DIFFERENCE)**

Null Hypothesis: D(SMI) has a unit root

Exogenous: Constant, Linear Trend

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.199259	0.0000
Test critical values:	1% level	-4.165756	
	5% level	-3.508508	
	10% level	-3.184230	

Table 5.7: **WITH CONSTANT (LEVEL)**

Null Hypothesis: UR has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.356701	0.0000
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

Table 5.8: **WITH CONSTANT AND TREND (LEVEL)**

Null Hypothesis: UR has a unit root

Exogenous: Constant, Linear Trend

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.438853	0.0002
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

Table 5.9: **WITH INTERCEPT (LEVEL)**

Null Hypothesis: INF has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.752731	0.0061
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

Table 5.10: **WITH TREND AND INTERCEPT (LEVEL)**

Null Hypothesis: INF has a unit root

Exogenous: Constant, Linear Trend

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.682717	0.0330
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

Table 5.11: **WITH CONSTANT (LEVEL)**

Null Hypothesis: GDP has a unit root

Exogenous: Constant

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.882936	0.0000
Test critical values:	1% level	-3.571310	
	5% level	-2.922449	
	10% level	-2.599224	

Table 5.12: **WITH TREND AND INTERCEPT (LEVEL)**

Null Hypothesis: GDP has a unit root

Exogenous: Constant, Linear Trend

Lag Length:0 (Automatic-based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.244563	0.0000
Test critical values:	1% level	-4.156734	
	5% level	-3.504330	
	10% level	-3.181826	

Appendix 5: Impulse Response Functions

Figure 5.6: **Response to Cholesky One S.D. Innovations**