DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF SOCIAL SCIENCES
DEPARTMENT OF ECONOMICS
ECONOMICS PROGRAM
MASTER'S THESIS

IS IT TIME FOR ACTION (?): LOSS MINIMIZATION IN CRISIS PREDICTION

Tuğba SAĞLAMDEMİR

Supervisor
Prof. Dr. Saadet KASMAN

İZMİR - 2013

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DECLARATION

I hereby declare that this master's thesis titled as "IS IT TIME FOR ACTION (?): LOSS MINIMIZATION IN CRISIS PREDICTION" has been written by myself in accordance with the academic rules and ethical conduct. I also declare that all materials benefited in this thesis consist of the mentioned resourses in the reference list. I verify all these with my honour.

Date ..../..../......
Tuğba Sağlamdemir

Signature

ABSTRACT

Master's Thesis

Is It Time For Action (?): Loss Minimization in Crisis Prediction

Tuğba SAĞLAMDEMİR

Dokuz Eylül University
Graduate School of Social Sciences
Department of Economics
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This thesis aims to design early warning systems, which predict currency, banking and debt crises, and determine the optimum threshold value to be applied on the prediction probabilities for determining the state of the economy as either tranquil, pre-crisis, or adjustment so as to minimize the loss of the economy. In predicting crises by using early warning systems, there exist two potential sources of loss for the economy: Missing a crisis and a false alarm. These sources are called as Type-1 and Type-2 errors respectively. In this study, after designing early warning system that predicts the status of the economy, a loss function is defined to calculate the loss, which arises due to the mentioned errors that might exist in the early warning system. This loss function takes the policy maker as an exogenous decision maker. This study, is not only constructing an early warning system for crisis prediction, but also providing the policy maker with an optimal threshold level for the predictions in order to obtain the optimum early warning system for both developing and developed countries. The data are taken from World Bank, IMF and OECD and span the years between 1980 and 2012. Multinomial logistic regression is used for crisis prediction. As an advantage, it prevents the 'post-crisis bias' problem; by this way the robustness of the analysis is also improved. The multinomial logistic regression is run for two different time windows 't-1, t, t+1' and 't, t+1, t+2' as t denoting the current year. With a threshold level of 20%, the system predicts 60% of the crises correctly for the time window of 't-1, t, t+1', whereas this number increases to 92% for the time window of 't, t+1, t+2'. In calculating the loss function, the threshold level to be applied on the predictions is swept from 0.01 to 1 (1% to 100%). Depending on the literature, 3 different values have been used for the relative risk aversion of the policy maker, which are $\theta = 0.2$, $\theta = 0.5$, and $\theta = 0.8$. According to the results, the lowest value of loss function is obtained at the highest rate of the policy maker's relative risk aversion and lowest rate of threshold level for both time windows. Depending on the results, it is possible to make the following generalization for policy offer: the policy

makers should give more importance to the cost of missing crisis and they should keep the threshold level at a lower rate in order to protect their economies against the loss that may arise due to the potential errors, which may be caused by the early warning system.

Keywords: Early Warning Systems, Currency Crisis, Banking Crisis, Debt Crisis, Post-crisis Bias, Multinomial Logistic Regression, Threshold Level, Loss Function, Ideal Early Warning System, Missing Crisis, Sending Wrong Signals, False Alarm

ÖZET

Yüksek Lisans Tezi

Önlem Alma Zamanı Mi (?): Kriz Tahminlemede Hatanın En Aza İndirgenmesi

Tuğba SAĞLAMDEMİR

Dokuz Eylül Üniversitesi

Sosyal Bilimler Enstitüsü

İktisat Anabilim Dalı

İktisat Programı

Bu tez çalışması, para, bankacılık ve borç krizlerini tahminlemek için erken uyarı sistemleri kurmayı ve kriz politikalarından doğan kaybı en aza indirmek üzere, ekonominin durumunu sakin, kriz öncesi veya kriz sonrası dönemleri olarak tanımlamak için kullanılacak olasılık tahminlerine uygulanacak en uygun eşik değerini tespit etmeyi amaçlamaktadır. Erken uyarı sistemleri ile kriz tahminlemede ekonomide kayıp oluşturacak iki olası sebep vardır: Kriz kaçırma ve yanlış uyarı. Bu sebepler, sırasıyla Tip-1 ve Tip-2 hatalar olarak adlandırılır. Bu çalışmada, ekonominin durumunu tahminleyen bir erken uyarı sistemi kurulduktan sonra, sistemde, bu belirtilen hatalardan kaynaklanan kaybı hesaplamak için bir "kayıp fonksiyonu" tanımlanmaktadır. Bu kayıp fonksiyonu, politika yapıcıyı dışsal bir karar alıcı olarak kabul eder. Bu çalışma, sadece kriz tahminleme için bir erken uyarı sistemi kurmakla kalmamakta, aynı zamanda, hem gelişmiş, hem de gelişmekte olan ülkelerde politika yapıcıya en uygun erken uyarı sistemini kurabilmek için tahminlemede kullanılacak en uygun eşik değerini sağlamaktadır. Çalışmada kullanılan veriler, Dünya Bankası, Uluslararası Para Fonu (IMF) ve Ekonomik Kalkınma ve İşbirliği Örgütü (OECD) veritabanlarından alınmıştır ve 1980 - 2012 yılları arasını kapsamaktadır. Kriz tahminlemede 'Çok Terimli Lojistik Regresyon' tekniği kullanılmıştır. Bir avantaj olarak, bu yöntem, "kriz sonrasi sapma" problemini önlemektedir. Analizin sağlamlığı, bu şekilde geliştirilmektedir. Regresyon analizi, t'nin şimdiki yılı belirttiği durumda, 't-1, t, t+1' ve 't, t+1, t+2' şeklinde iki farklı zaman penceresi için koşturulmuştur. %20 eşik değeri ile sistem 't-1, t, t+1' zaman penceresi için, krizleri %60 başarıyla tahmin ederken, aynı eşik değerinde 't, t+1, t+2' zaman penceresi için başarı oranı %92'ye yükselmektedir. Hata fonksiyonu hesaplanırken, tahminlemede kullanılan eşik değeri 0.01'den 1'e kadar eşit aralıklarla değiştirilmiştir. Literatüre dayanarak, politika yapıcının "bağıl risk savma" (θ) parametresi için *0.2, 0.5 ve 0.8* olmak üzere 3 farklı değer kullanılmıştır. Çalışma sonuçlarına göre, kayıp fonksiyonunun en düşük değeri, her iki zaman penceresi için de, bağıl risk savmanın en

yüksek, eşik değerinin en düşük olduğu durumlarda elde edilmektedir. Sonuçlara dayanarak, politika önerisi için şu genelleme yapılabilir: Politika yapıcılar, kriz kaçırmanın bedelini daha fazla önemsemeli ve erken uyarı sisteminde oluşabilecek hatalardan kaynaklı ekonomik kayıpları en aza indirebilmek için eşik değerini düşük tutmaya çalışmalıdır.

Anahtar Kelimeler: Erken Uyarı Sistemleri, Para Krizleri, Bankacılık Krizleri, Borç Krizleri, Kriz Sonrası Sapma, Çok Terimli Regresyon, Eşik Değeri, Kayıp Fonksiyonu, İdeal Erken Uyarı Sistemi, Kriz Kaçırma, Yanlış Uyarı Yollama, Yanlış Uyarı

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INTRODUCTION

The hypothesis of this study is formed on the trade-off problem between the cost of missing a crisis and taking pre-emptive action in the case of a false alarm. This trade-off problem is important for the following reasons: Crises are events that have been re-occurring since the 14^{th} century and policy makers could not prevent the outbreak of crises from that time. This is the reason why crisis prediction is crucial for the whole economy. In this study, it is aimed to answer the following question: Is there any systematic, general approach in constructing an early warning system, which minimizes the cost of taking pre-emptive action in case of a false alarm or the cost of missing a crisis while predicting either a currency, banking or debt crisis, both for developing and developed economies.

Economic crisis, as being one of the common problems of the world, has a history that dates back to 14^{th} century in England (Reinhart and Rogoff, 2008b: 1-53). Since the crisis creates a destructive impact on the economy, both policy makers and academics search for policies to avoid the crisis. If the economy consisted of mechanisms, which followed the same rules and did not change until the policy makers made any regulations, they would achieve their aim. However, the reality is different. There are many actors in the system and each of them makes different contributions. Due to this fact, the measures, which are taken to avoid the crisis, do not work.

Once it is accepted that the economic crises are situations which the economies cannot escape from, the optimum solution turns out to become predicting the coming crisis before it hits the economy, in order to protect the whole economic system as much as possible. As a consequence, the requirement for predicting crisis before its outbreak arises.

There exist quite a large number of studies on predicting crisis in the literature. They construct early warning systems for predicting crisis. Since their aim is to predict crisis, they construct their systems so as to catch all types of deviations of the economy from normal trend. While designing the early warning system to predict all types of crisis, these studies generally ignore the cost of taking pre-emptive action in the case of a false alarm compared to the cost of missing a crisis. This depends on the assumption that the policy makers think that the cost of missing a crisis is more catastrophic than the cost of taking pre-emptive action in the case of a false alarm (Bussiere and Fratzscher, 2002: 19-47). Although they continue their researches with this assumption, they also point out that there exists a trade-off between missing a crisis and taking pre-emptive actions. Bussiere et al (2008) try to find an ideal solution for this trade-off for an early warning system, which is designed to predict currency crisis for 20 emerging economies. They were only partially successful in finding satisfactory results, since they could not form a set of general construction rules for the optimal early warning system. Nevertheless, they still offered valuable solution techniques for the decision makers.

The previous studies generally emphasize the similar indicators, which come from macroeconomic and financial data. Also, more or less, they usually apply the same techniques, which are being used from the very beginning of the early warning system studies. Every analysis with the aim of constructing an early warning system is a step to achieve higher prediction power; however, since economy has a very dynamic structure, both the prediction techniques and the data to be used in the estimation process have to evolve through time to improve the ability of catching the alterations in the system. In that respect, importance of working on a greater data set, which spans more countries and a wider time period with different types of techniques, increases. By this thesis, it is aimed to construct a system, which includes all related variables and the widest time period, as much as the data source allows. Also, the multinomial logistic regression is run not only for just one but two different time windows.

Furthermore, the target is to construct an early warning system, which is able to predict all types of crisis (either currency, banking and debt) by using the indicators used in the previous studies in the literature. Since the crisis is the common problematic part of the economy for the countries, it is worth to search for designing a mechanism, whose target is to find the best solution for solving the trade-off problem between the cost of taking pre-emptive actions in the case of a false alarm and the cost of missing a crisis. Bussiere et al. (2008) is the milestone study, which aims to find a solution to solve this trade-off problem. Although the authors make important contributions to solving of the problem, they run their estimations for only the currency crisis, and for 20 emerging economies for the years between 1993 and 2001 only. Their predictions are done depending on one time window only, which is 't-1, t, t+1'. Since their data set is restricted in terms of crisis types, spanned time interval, used time windows and countries; their results are valid only for restricted cases.

In this study, the analysis on the crisis prediction is separated into two cases: In the first case, the crisis is predicted by running a multinomial logistic regression over time window of 't-1, t, t+1' where 't' denotes the current year of investigation, 't-1' is the year before the current one and 't+1' is the year after it. Hence, given that a crisis has occurred at time 't', then the behavior of the variables within 't-1' to 't+1' is analyzed. That is, the values both before and after the crisis are taken into consideration. In the second case, again the multinomial logistic regression technique is used. However, the time window is now changed to 't, t+1, t+2'. In this case, the analyzed time window covers the current year and two consecutive years after it. Hence, the behavior of the variables before the crisis is not taken into consideration but the focus is on their current and future values. For both time windows of multinomial logistic regression, the estimation is done for evaluating both the in sample and out of sample performances.

In obtaining the optimal early warning system, which minimizes the loss originating from missing a crisis or giving a false alarm, determining the correct threshold level to be applied on the prediction results is vital. To achieve this goal, a loss function is defined, which assumes the decision maker as an exogenous factor and the sources of the loss are divided into two categories as follows: The first category is the cost of missing a crisis and the second category is the cost of taking pre-emptive action for preventing crisis in the case of a false alarm. The loss function is estimated for all threshold levels that is, the threshold value is swept from 0.01 to 1. In the definition of the loss function, the actions of the decision maker are modeled by assigning some weights to both the cost of a missed crisis and the cost of pre-emptive actions for a false alarm. In this study, three different values for those weights are analyzed as one value representing the case in which the weight of the cost of a missed crisis is higher, one representing the case in which the cost of pre-emptive actions is higher and the third representing the case in which the weights for each are equal. Also, the estimation is run for both time windows of early warning system to make a comparison between time windows' successes in minimizing the value of loss function.

In this thesis, the following questions are answered: Is it possible to design an early warning system, which minimizes the cost of missing a crisis and the cost of taking pre-emptive actions, while predicting currency, banking and debt crisis successfully at the same time? Are the results appropriate to establish a general set of rules for constructing ideal early warning systems? Does the time window, which is used in the multinomial logistic regression for prediction, make any change for the value of loss function or both time windows give the same results? Which time window is more suitable to be used in crisis prediction to attain a lower loss in terms of cost?

Applying the procedure described above, the empirical results show that it is possible to design an early warning system, which predicts currency, banking and debt crisis successfully with the minimum amount of loss due to missing of a crisis or taking pre-emptive actions. Also, for both time windows, the estimation results go hand in hand, which allows us to form a general set of rules for constructing ideal early warning systems. The loss function takes different values for each time window and the time window of 't-1, t, t+1' is more appropriate to be used in crisis prediction to attain lower loss in terms of cost.

This thesis is organized as follows: Chapter 1 analyzes the literature. Chapter 2 gives details on the data and methodology. Chapter 3 reviews empirical analysis results. The study ends with the Conclusion.

CHAPTER ONE
LITERATURE SURVEY

The economy is a complete system, which consists of different dynamics. As the countries' economies getting integrated each other in terms of financial dependence each other, the economic decisions which are taken form one country turns to be an important indicator for whole economies over the world. As a result of this, this system needs to control to prevent from out breaking a crisis. The policy makers try to control and arrange any variation in each countries for every indicator, which may affect the other components and cause the whole system to collapse, by utilizing the tools and mechanisms they have in hand.

Although there are many regulatory mechanisms, which arrange and supervise the system, unexpected changes still do appear. These changes sometimes become so uncontrollable that they drive the economy into crisis. These crises may be the result of some already existing dynamics or may arise due to a new dynamic, which has recently been introduced to the system and has become crucial in an ongoing basis on the economic conditions.

As a matter of fact, the economic crisis history is as old as the history of economy. Since there are many indicator factors constituting the whole economy - and new indicators get involved in this system continuously - it is impossible to think of an economy, which never suffers from an economic crisis. On the other hand, the most appropriate solution for reducing the destructive impact of a crisis on the economy is to predict the coming of it and take the required precautions so as to protect the economy as much as possible. This indeed is the motivation behind designing an Early Warning System, aim of which is to predict a crisis before it hits the economy.

There are different types of economic crises as currency crisis, banking crisis and debt crisis. The policy makers generally tried to construct Early Warning Systems for each type of crisis on its own. After mid 90s, the currency crisis turned out to become a common problem of the economic systems. This crisis type is analyzed by Kaminsky et al (1998) and in this analysis, a new non-parametric approach is constructed, which is also called as the signal approach (Kaminsky et al., 1998: 1-48). This approach is prominent in the field of early warning systems, whose prediction power is 70% in the in-sample analysis. By this study, it has been shown that it was possible to predict a crisis with a non-parametric approach. After this analysis, the early warning system literature has been introduced a new term as "false signal", standing for the cases in which the system warns about a coming crisis but there is no upcoming crisis indeed.

Then researchers sought for new estimation techniques to construct early warning systems. Berg et al (1999a) use the same data set and crisis definition as Kaminsky et al to work on the currency crisis (Berg and Pattillo, 1999a: 561-586). However, their estimation technique is the probit approach for designing the early warning system, where the dependent variable takes the value of one for the case of a coming crisis and zero for all other cases. The probit approach is more practical than the signal approach since it allows testing the statistical significance and coefficient constancy overtime and countries.

In addition to the probit approach Demirguc-Kunt et al. (1997) introduce a new estimation tool (Demirguc-Kunt, 1997: 3-17). They try to find the main reason behind the banking crisis by working on both developing and developed countries. They apply multivariate logit model to identify the determinants of the banking crisis.

Since the important thing is not only constructing the early warning system but also predicting the crisis with the highest success ratio, the literature seek for new techniques, new data sets and indicators to increase their prediction power. Binomial logit is another technique used but its results suffer from post-crisis bias which is described in Section 2.2.

Bussiere et al (2002) construct an early warning system aiming for predicting currency crisis by using the estimation technique of multinomial logistic regression (Bussiere and Fratzscher, 2002: 19-47). Since they criticize the prediction power of the binomial logit model, their analysis consists of both binomial and multinomial logistic regression models. The data set they use contains 32 emerging economies and spans the years from 1993 to 2001. According to their estimations, the binomial logistic regression predicts the crisis entry periods with a success ratio of 56,9% and multinomial logistic regression estimates the same periods with 65,5% success. After their contribution, the multinomial logistic regression technique replaces the binomial logistic regression in the early warning system literature.

Although the early warning system techniques are generally parametric, there are some analyses, which compare the prediction power of the different methods such as the one done by Peltonen (2006) for predicting currency crisis (Peltonen, 2006: 9-22). In this study, two early warning systems are constructed by using two different approaches: probit approach, which is parametric, and artificial neural network (ANN) model as a non-parametric approach. Their data set comprises eight exogenous indicators, and the time interval spans the period between 1980 and 2001 for 24 emerging economies. The main contribution of this paper is that, it compares the prediction power of probit model with Artificial Neural Network approach for in sample and out of sample performance in predicting currency crisis. Then it is shown that the ANN approach outperforms the probit model for predicting currency crisis regarding the in-sample performances, but both methods' out-of-sample performances are weak.

Although most of the early warning systems are designed to predict the currency crisis, after 2000s, with the financial liberalization and globalization, the reason of the economic crises do change with the structure of the economy. As a consequence of this change, different types of crises emerge and attract the literature's attention. Manasse et al (2003) constructed an early warning system with the aim of predicting debt crisis (Manasse et al., 2003: 8-32). Their data set consists of 47 markets and the time interval spans years from 1970 to 2002. In this analysis, both a non-parametric approach - Classification and Regression Tree (CART) - and a parametric approach - binomial logistic regression - are applied and their prediction powers are compared. According to the results, binomial logistic regression predicts 74% of the crises where CART predicts 89% of the crisis entries. On the other hand, CART sends more false alarms then the binomial logistic regression. No out-of-sample analyses are applied.

The debt crisis is analyzed by many researchers as Bruner et al (1987) and also the debt crisis is also analyzed by Roubini et al (2005) by CART as well, using 47 countries' data, which belongs to the period of 1970 to 2002 (Manasse and Roubini, 2005: 3-26). 10 exogenous variables are used for the estimation process and the prediction power of this model is 85% for the in-sample performance and 35% for the out-of-sample performance.

To estimate the debt crises, more techniques and crisis definitions are used with the aim of increasing the estimation power. One of them is constructed by Ciarlione et al (2005) (Ciarlone and Trebeschi, 2005: 376-395). In this analysis, they use multinomial logistic regression to predict the crisis. Also, they run a binomial logistic regression to make a comparison between the estimation powers of these two models. By using 28 countries' data, which also span the years from 1980 to 2002, they find that, with the binomial logistic regression's in-sample prediction power of the model is 72,5%. For the same data set, the in-sample prediction power increases to 76% with the multinomial logistic regression. They do not make an out-of-sample performance analysis for the models. One year later, again Ciarlione et al (2006) construct a new early warning system to predict debt crisis (Ciarlone and Trebeschi, 2006: 21-24). The debt crisis definition and multinomial logistic regression construction is different compared to their previous analysis. This analysis uses the same data set, but their prediction power is 78% for the in-sample performance and 70% for the out-of-sample performance.

For all the studies mentioned above, the early warning system's prediction power is determined depending on the model's power of signaling crisis, adjustment and tranquil periods correctly. In the very beginning, the most important thing about the early warning systems was their existence and capability of giving signals about an upcoming crisis. Eventually, it has been realized that giving a signal was not the only important thing. Accuracy of the signal was very important as well. If the system gives a signal for crisis but the economy does not experience a crisis, this causes a loss originating from the unnecessary crisis policies. On the other hand, if the system does not signal for any upcoming crises, but the economy experiences a crisis, then the economy will have to pay for the cost of this missed crisis. Bussiere and Frazcher emphasized this problem in their groundbreaking study in 2002 (Bussiere and Fratzscher, 2002: 19-47). The researchers revealed that there is a trade off problem in choosing an optimal threshold level. In the case of the decision maker choosing a lower threshold level, the model will send more signals. In this situation the economy might face with the cost of taking unnecessary pre-emptive actions. However, if the decision maker sets a higher threshold level, the economy may come across the situation of missing crisis.

After Bussiere and Fratzcher emphasized this problem, they continued to work on the early warning systems. The researchers proposed an early warning system in 2006, whose estimation technique was multinomial logistic regression using the time window 't-1, t, t+1' for 20 emerging economies to predict currency crisis (Bussiere and Fratzscher, 2006: 953-973). The researchers used this system's results to find an optimal threshold level to solve the trade off between low threshold level and high threshold level in their research in 2008 (Bussiere and Fratzscher, 2008: 111-121). They reached to the following results: A higher degree of risk aversion induces modelers to choose a longer time horizon H and a lower threshold level T. Also, for any given degree of risk aversion, a choice of a longer time horizon H optimally requires a higher threshold level T and vice versa.

This trade-off problem is also analyzed by the following studies: Sarlin (2013) replicates the Berg et al.'s (1999) early warning system to catch currency crisis and Lo Duca et al's (2012) early warning system to catch systemic financial crisis (Sarlin, 2013: 5-19; Lo Duca et al., 2012: 10-20). After making predictions with the early warning systems, the researchers introduce a new loss function which accounts for unconditional probabilities of the classes, computes the proportion of available usefulness that the model captures and weights observations by their importance for policymaker. They emphasize the importance of classifying observations of most relevant entities to reach the better results.

The statistical significance of early warning systems is analyzed not only by the researchers who worked with parametric models, but also by the researchers who worked with non-parametric models. El Shagi et al. (2013) analyze the statistical significance of signal approach (El Shagi et al., 2013: 76-103). They use the data set of Kaminsky and Reinhart (1999) to predict currency and banking crisis (Kaminsky and Reinhart, 1999: 473-500). Also, they take the data from Alessi and Detken (2011) to cover asset price bubbles (Alessi and Detken, 2011: 520-533) and from Knedlik and Von Schweinitz (2012) to cover sovereign debt crises (Knedlik and Von Schweinitz, 2012: 726-745). They reached to the following results: Previous applications of the signals approach yield economically meaningful results, the indicators which are found to be significant in sample usually perform similarly well out of sample. Also the researchers created new composite indicators to predict the early warning systems and they found that composite indicators aggregating information contained in individual indicators add value to the signals approach.

As the contribution to the literature, by this analysis, it is aimed to find the ideal threshold levels to be used in order to solve the trade off problems, which arise from the construction of the early warning systems. The estimation tool used for constructing the early warning systems is multinomial logistic regression with the time windows of 't-1, t, t+1' and 't, t+1, t+2'. The data set consists of 67 countries and spans the years between 1980 and 2012, to predict currency, banking and debt crisis.

CHAPTER TWO
DEFINITIONS, DATA AND METHODOLOGY

2.1 DEFINITIONS AND DATA

In predicting crisis, there are many important steps in the construction part and the first one of them is defining the crisis conditions. The next step after categorizing the conditions is the prediction of the coming of a crisis. At this point, the most important thing is choosing the right indicator variables. The main goal of crisis prediction is to construct a model, which is capable of catching upcoming crises with the minimum possible number of misses. Therefore, the system needs some precise threshold, which helps in charting out. There are some basic questions answers of which help in leading the variation of the model. These questions are as follows:

- What is the definition of the crisis?
- Which countries constitute the research area?
- What is the time interval and which explanatory variables are in use?

By answering these questions, the general outline will be designed and then it will be easy to construct the model by using these answers. Basically, there are three kinds of economic crises as banking crisis, currency crisis and debt crisis. They differ from each other in terms of some basic causes and results but their general effect is the same: lowering nations' welfare. Motivated by this fact, the system proposed in this study aimed to predict all these three types of crises. A brief definition for each type of crisis can be given as follows (Reinhart and Rogoff Online Resources):

• **Currency crisis:** The economic situation is defined to be a currency crisis if the annual inflation rate is 20 percent or higher and the annual depreciation versus the United States dollar is 15 percent or more.

• **Banking Crisis:** If one or both of the following two conditions hold, the economy is said to have a banking crisis:

(i) Bank runs that lead to the closure, merging or takeover by the public sector of one or more financial institutions.

(ii) If there are no runs, the closure, merging, takeover or large scale government assistance of an important financial institution (or group of institutions) that marks the start of similar outcomes for other financial institutions.

• Debt Crisis: It is identified in the case of a failure to meet a principal or interest payment on the due date (or within the specified grace period). The episodes also include instances where rescheduled debt is ultimately extinguished in terms less favorable than the original obligation. In addition to this condition, the situations of banks being forced to freeze their deposits or forcible conversions of such deposits from dollar to local currency are considered to be debt crisis conditions as well. These conditions for different types of crises cases have been defined in accordance with the previous studies of Reinhart and Rogoff to identify currency, banking and debt crises (Reinhart and Rogoff Online Resources).

The data set is formed from 85 exogenous variables, which include all the variables from studies on predicting crisis in the literature. The overall data set, classified according to their categories, is given in Table 1.

While grouping the variables, the categorisation is done according to prior studies (Kaminsky et al., 1998: 1-48).This data set includes the period between 1980 and 2012 for the countries given in Table 2:

Table 1: Data Set Classified According to Categories

Source	Set of Variables
Capital Account	Net open position in the foreign exchange to capital ratio, FDI, total reserve growth, FDI to GDP
Current Account	Exchange rate, export, import, current account balance, export growth rate, import growth, current account to GDP, Deviations of real exchange rate from trend
Debt Profile	Household debt to GDP, short term debt to international reserves, domestic credit to private sector, interest payment on total external debt, total external debt stocks, short term external debt stocks, short term debt to total reserves, short term debt to total external debt , interest payments on short term external debt, central government debt as percentage of GDP, private non-guaranteed external debt stocks, public and publicly guaranteed external debt stocks, bank non-performing loans to total gross loans, total debt service percent of exports, interest payments on long term external debt, total external debt to GDP, external debt to exports, international reserve to total external debt, short term debt to GDP, total external debt to total reserves, short term debt international reserve growth, real domestic credit growth, interest payments on external debt to international reserve, interest payment on short term debt to GDP
International Variables	Foreign exchange reserves, use of IMF credit, portfolio equity net inflows, net ODA received

Source	Set of Variables
Financial Liberalization	Deposit rate, bank liquid reserve to bank asset ratio, domestic credit provided by banking sector percent of GDP, deposit insurance, interest rate spread, risk premium on lending, S&P global equity indices (annual percentage change), stocks traded (total value), stocks traded turnover ratio, international reserve growth
Other Financial Variables	Money supply, return on equity, liquid asset to total asset, treasury bill rate, liquid asset to short term liabilities, non performing loans to total gross loans, return on asset, sectoral distribution of total loans(deposit takers), sectoral distribution of total loans(residents), bank capital to asset ratio, inflation volatility, change in terms of trade, the ratio of M2 reserve to international reserve
Real Sector	Industrial production, GDP, unemployment rate, GDP growth, trade in services percent of GDP, real interest rate, inflation, GDP per capita, gross saving percent of GDP
Institutional variables	Capital adequacy ratio, degree of openness to international trade, financial requirement to total reserve
Fiscal Variables	Short term interest rates of government securities and government bonds, medium- long term government securities and government bonds, government revenue excluding grants percent of GDP, government expense percent of GDP, tax revenue percent of GDP, fiscal surplus to GDP

Table 2: Countries Used as Data Source

Countries
Algeria, Argentina, Austria, Bolivia, Brazil, Canada, Chile, China, Colombia, Costa Rica, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Finland, France, Germany, Greece, Guatemala, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Jordan, Kazakhstan, Korea, Latvia, Lithuania, Luxembourg, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Singapore, Slovakia, South Africa, Spain, Sweden, Switzerland, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, United States , Uruguay, Venezuela

Multinomial logit regression is the methodology, which is used in constructing the early warning system. In this model, the system needs to use sufficiently enough data to make prediction.

The total number of observations in the whole data set is 1974. However, due to the fact that some of the variables have missing values for some of the countries for a few years, the number of observations used in the analysis decrease from 1974 observations to 219 observations for 't-1, t, t+1' case and to 183 observations in 't, t+1, t+2' case.

The dependent variable of the regression indicates the state of the economy identified for three different cases as pre-crisis, crisis and tranquil periods. The dependent variable is generated over a crisis indicator variable, which takes the value of 1 for the years with crises and value of 0 otherwise. (The details of the construction of time windows and the dependent variables are given in Chapter 3). These periods of crisis, pre-crisis and tranquility are created in accordance with the previous studies in the crisis predicting literature (Glick and Hutchison 1999: 6-23; Manasse and Roubini, 2009: 192:205; Laeven and Valencia, 2008: 5-7; Reinhart and Rogoff Online Resources).

While running the estimations, the approach proposed by Ciarlone et al (2005, 2006) is followed. In the first step separate multinomial logistic regressions have been run for each single variable on its own to check their statistical significance. The main estimation is run by only including those, which were proven to be significant at this first stage. In the estimation, some groups of these variables had exhibited similar properties in terms of their effects on the economy. As a result of these similarities, it was possible to create some sub-groups from these variables in accordance with the prior studies for currency, banking and debt crises (Berg and Pattillo, 1999b: 107-138; Bussiere and Fratzscher, 2002: 19-47; Kaminsky et al., 1998: 1-48; Demirguc-Kunt, 1997: 3-17; Manasse et al., 2003: 8-32; Ciarlone and Trebeschi, 2005: 376-395; Ciarlone and Trebeschi, 2006: 21-24).

After these groups were constructed, the multinomial logit regressions were run for each group for predicting crises. After this, for every group top three best performers, showing the highest variation passing through from tranquil period to pre- crisis period in terms of odds ratio, were selected for the next step. For some of these groups, the mlogit regression could not converge to a solution because of either insufficient number of observations or concavity problems. Such groups have been further divided into smaller sub-groups until a successful mlogit run could be achieved. This method of creating groups and selecting best performers for the next step continued up until reaching the final working combination of variables whose odds ratios showed the highest deviation while passing from tranquil period into the pre-crisis period with in 95% confidence interval.

Finally, all sub-groups' best performers were put together to create the set of main independent variables to be used in the model for predicting crisis. In the analysis part the prediction was done according to two different time windows as 't-1, t, t+1' and 't, t+1, t+2' where t denotes the current year of concern. Since the estimation of these two models depended on different time windows, the independent variables, which were used in these models, are not same.

The final group, which is used in the case of time window "t-1, t, t+1" consists of the following variables: Exchange rates, trade in services (% of GDP), real interest rate, inflation (CPI), bank liquid reserve to bank asset ratio, domestic credit provided by banking sector (% of GDP), GDP per capita, degree of openness to international trade, total reserve growth (%), treasury bill rate, FDI to GDP, inflation volatility, risk premium on lending.

The final group, which is used in the case of time window "t, t+1, t+2" is formed from the following variables: International reserve growth, current account to GDP, total reserve growth (%), FDI to GDP, Change in terms of trade, Domestic credit to private sector (% of GDP), real domestic credit growth, import growth, degree of openness to international trade, export growth rate, S&P Global Equity Indices, Tax revenue (% of GDP), Bank capital to asset ratio (%), Interest rate of government securities and bonds, Bank liquid reserve to bank asset ratio, Central government debt as percentage of GDP.

After the early warning system is constructed, both the in-sample, and out-of-sample performances are estimated. The definition of the periods of the economy as pre-crisis, adjustment or tranquil depends on the threshold level, which is applied on the probability values of the prediction results obtained from the early warning system. This is the most crucial factor for evaluating the predictive power of the early warning system, since its success or failure of estimating the status of the economy will be determined with respect to this threshold value. If the early warning system uses a low threshold level, it will send more signals since it will evaluate all types of variations as a crisis signal. Hence, a low threshold level will raise the number of wrong signals. These conditions are identified as Type-2 error.

On the other hand, a high threshold level will send fewer signals, which means it will accept the variations as cyclic movements in the economy. As a result of this, it will interpret such kind of movements as the normal trend of the economy. Consequently, increasing the threshold level increases the number of crises missed by the early warning system. These kinds of conditions are identified as Type-1 error.

If a high threshold level is used in prediction, the probability of experiencing a Type-1 error is very high. If the policy maker uses a high threshold level to predict crisis, he might fail to realize a coming crisis and accept the variations as a normal trend. As a result of this, a crisis might hit the economy without the policy maker having taken the necessary actions to protect the economy from the destructive effects of that crisis. Consequently, a missed crisis will make the economy pay a great cost.

On the other hand, if a low threshold level is used in prediction, the probability of experiencing a Type-2 error is very high. If the policy maker uses a low threshold level to predict crisis, he might consider a normal variation in the economy as a coming crisis since the early warning system will signal for it. As a result, he might take some pre-emptive actions to protect the economy from that crisis. However, since there exists no upcoming crisis for the economy, these pre-emptive actions will become unnecessary and it is a known fact that such unnecessary precautions have an important cost for the economy (Bussiere and Fratzscher, 2006: 953-973). Hence, the economy will now have to pay for that cost of a wrong signal.

Given the explanations above, determination of the optimum threshold level to be used for the probabilities in deciding whether the economy is in tranquil, pre-crisis, or crisis period becomes crucial. In order to achieve that, in this study, the threshold level has been swept from 0.01 to 1 in order to find the ideal early warning system with the optimal threshold value. As a significance figure for the goodness of fit analysis, three of these threshold values (20, 50 and 80 percent) were selected in accordance with the related literature (Bussiere and Fratzscher, 2008: 111-121).

In this study the aim is to find an ideal threshold level to minimize the loss, which might arise because of the both Type-1 and Type-2 errors by using an early warning system. The early warning system uses multinomial logistic regression, which is run over two different time windows as 't-1, t, t+1' and 't, t+1, t+2' to predict crisis. The data set used for finding that ideal system for crisis prediction and loss minimization consists of 67 countries and spans the time period between 1980 and 2012.

In order to find the mentioned optimum threshold level, a loss function is used as described in the estimation part of this paper, which takes both Type-1 and Type-2 errors into consideration as a cost creator for the economy.

2.2 METHODOLOGY

There are different kinds of estimation techniques in the early warning systems. These techniques are divided into two main groups as parametric and non-parametric techniques. Since the variables are assumed to be statistically independent, using a parametric estimation method is much more suitable for constructing an early warning system.

Logistic regression is one of the parametric techniques, which has many advantages as follows:

- Logistic regression allows properties of a linear regression model to be exploited.
- The logistic regression value can vary between $-\infty$ and $+\infty$. Although, the model coefficients' value change $-\infty$ and $+\infty$, the probability remains 0 and 1, by this way it gets easy to make interpretation and analysis depending on the data.

- The logit model can directly affect the odds ratio, as an advantage of this property, the changes in the model can be totally reflected to the ratio (Online Resources PennState University).

Logistic regression has two branches as binomial logistic regression and multinomial logistic regression. Binomial regression function analyzes the economy by separating it into crisis and adjustment periods. This method has been used in many studies to predict crisis (Ciarlone and Trebeschi, 2005: 376-395; Manasse et al., 2003: 8-32; Davis and Karim, 2008b: 35-47). Although the models in these papers predicted many crises, they were ridden by the post crisis bias.

Post-crisis bias means that, while predicting a crisis, the independent variables are analyzed depending on their values during and directly after a crisis. However, the aim for constructing early warning systems is predicting crises before they hit the economy. The most suitable way of doing this is comparing the variation of the variables before a crisis compared to their values during tranquil periods, when their values are sustainable. But a binomial logit model compares the pre-crisis observation with that in both the tranquil periods and crisis/adjustment periods. That is, the binomial logit model does not differentiate the tranquil period from an adjustment period. This induces an important bias, as the variation of the independent variables is very different during tranquil times as compared to crisis/recovery period.

There are two ways to overcome this post-crisis bias. The first one is dropping all crisis/adjustment observations from the model and the second way is using a discrete dependent variable, which gives more than two outcomes: multinomial logistic regression (Bussiere and Fratzscher, 2002: 19-47).

The setup of the multinomial regression model is the same as that in logistic regression; the key difference is that, the dependent variable of logistic regression is formed from two outcomes whereas the dependent variable of multinomial logistic regression consists of more than two possible outcomes.

In order to explain the logistic regression, logistic function has to be introduced as:

$$\pi(x) = \frac{e^{(\beta_0+\beta_1 X_1+e)}}{e^{(\beta_0+\beta_1 X_1+e)}+1} = \frac{1}{e^{-(\beta_0+\beta_1 X_1+e)}+1}, \tag{2.1}$$

$$g(x) = \ln \frac{\pi(x)}{1-\pi(x)} = \beta_0 + \beta_1 X_1 + e, \tag{2.2}$$

$$\pi(x)/1-\pi(x) = e^{\beta_0+\beta_1 X_1+e} \tag{2.3}$$

The logistic function takes values from negative infinity to positive infinity and the output value changes between 0 and 1.

In these equations, $g(x)$ represents the logit function of given predictor X. "ln" present the natural logarithm, $\pi(x)$ gives the probability of being in a case, β_0 is the intercept from the linear regression equation. $\beta_1 X_1$ is the regression coefficient multiplied by some value of the predictor, and base e means the exponential function. The "e" in the linear regression equation stands for the error term.

To apply a logistic regression model, a series of N observed data points is needed. Each data point i, consists of a set of M explanatory variables from $x_{1,i}$ to $x_{M,i}$ and associated dependent variable Y_i.

In this model, it is assumed that the dependent variable Y is a random variable distributed according to the Bernoulli distribution. Each outcome of the dependent variable is determined by an unobserved probability p_i, which is special to the outcome itself but also connected to the explanatory variables as well. The overall picture for the logistic regression can be explained by the following equations (Greene, 2003: 16):

$$\begin{aligned} Y_i|x_{1,i},...,x_{m,i} &\sim \text{Bernoulli}(p_i) \\ \mathbb{E}[Y_i|x_{1,i},...,x_{m,i}] &= p_i \\ Pr(Y_i|x_{1,i},...,x_{m,i}) &= \begin{cases} p_i, & \text{if } Y_i = 1 \\ 1-p_i & \text{if } Y_i = 0 \end{cases} \\ Pr(Y_i|x_{1,i},...,x_{m,i}) &= p_i^{Y_i}(1-p_i)^{(1-Y_i)} \end{aligned} \tag{2.4}$$

The logistic regression can be designed by modeling the probability value of p_i using a linear predictor function. Hence, p_i will be a linear combination of the explanatory variables and a set of regression coefficients that are specific to the model.

The predictor function $f(i)$ for a data point i will be in the following form:

$$f(i) = \beta_0 + \beta_1 x_{1,i} + ... + \beta_M x_{m,i} \tag{2.5}$$

$\beta_0, ..., \beta_M$ are the regression coefficients and each gives the relative impact of a particular explanatory variable on the dependent variable. If,

- the regression coefficients $\beta_0, \beta_1, ..., \beta_k$ are grouped into a single vector $\boldsymbol{\beta}$ of size $k+1$;
- for each data point I, an additional explanatory variable $x_{0,i}$ is added, with a fixed value of 1, similar to the intercept coefficient β_0;

- the explanatory variables $x_{0,i}, x_{1,i}, ..., x_{k,i}$ are grouped into a single vector $\boldsymbol{X_i}$ of size $k+1$

then the linear predictor function turns into

$$f(i) = \boldsymbol{\beta . X_i} \tag{2.6}$$

The basic setup of the multinomial logistic regression is similar to that of the logistic regression. However, the dependent variable for a multinomial logistic regression is a categorical variable that is, it has more than two discrete possible outcomes. For multinomial logistic regression the probability of observation i having the outcome k is given by the linear predictor function $f(k,i)$ as following:

$$f(k,i) = \beta_{0,k} + \beta_{1,k}x_{1,i} + \beta_{2,k}x_{2,i} + ... + \beta_{M,k}x_{M,i} \tag{2.7}$$

$\beta_{m,k}$ is the regression coefficient that relates the m^{th} explanatory variable with the k_{th} dependent variable outcome. As with the same in the logistic regression function, the predictor function can be written as;

$$f(i) = \boldsymbol{\beta_k . X_i} \tag{2.8}$$

$\boldsymbol{\beta_k}$ is the set of regression coefficients related with outcome k and $\boldsymbol{x_i}$ is the set explanatory variables related with observation i.

To clarify the multinomial logistic model, one can assume that the multinomial logistic regression for a dependent variable with K different possible outcomes is like running a series of K-1 independent binomial logistic regressions in which one outcome is chosen as the base and the rest K-1 outcomes are separately regressed relative to the base outcome. In the case of the last outcome "K" being selected as the base, the probabilities would be calculated as follows:

$$\begin{aligned}
\ln \frac{Pr(Y_i = 1)}{Pr(Y_i = K)} &= \boldsymbol{\beta_1 . X_i} \\
\ln \frac{Pr(Y_i = 2)}{Pr(Y_i = K)} &= \boldsymbol{\beta_2 . X_i} \\
&.... \\
\ln \frac{Pr(Y_i = K-1)}{Pr(Y_i = K)} &= \boldsymbol{\beta_{K-1} . X_i}
\end{aligned} \tag{2.9}$$

Separate set of regression coefficients are introduced, one for each possible outcome. After exponentiation of both sides of the equations and solving, the resulting probabilities would be:

$$\begin{aligned} Pr(Y_i = 1) &= Pr(Y_i = K)e^{\boldsymbol{\beta_1}.\boldsymbol{X_i}} \\ Pr(Y_i = 2) &= Pr(Y_i = K)e^{\boldsymbol{\beta_2}.\boldsymbol{X_i}} \\ &\cdots. \\ Pr(Y_i = K-1) &= Pr(Y_i = K)e^{\boldsymbol{\beta_{K-1}}.\boldsymbol{X_i}} \end{aligned} \tag{2.10}$$

Since the sum of the K probabilities is equal to 1, the probability of the base outcome will be:

$$Pr(Y_i = K) = \frac{1}{1 + \sum_{k=1}^{K-1} e^{\boldsymbol{\beta_k}.\boldsymbol{X_i}}} \tag{2.11}$$

The rest of the probabilities can be found as follows:

$$\begin{aligned} Pr(Y_i = 1) &= \frac{e^{\boldsymbol{\beta_1}.\boldsymbol{X_i}}}{1 + \sum_{k=1}^{K-1} e^{\boldsymbol{\beta'_k}.\boldsymbol{X_i}}} \\ Pr(Y_i = 2) &= \frac{e^{\boldsymbol{\beta_2}.\boldsymbol{X_i}}}{1 + \sum_{k=1}^{K-1} e^{\boldsymbol{\beta'_k}.\boldsymbol{X_i}}} \\ &\cdots \\ Pr(Y_i = K-1) &= \frac{e^{\boldsymbol{\beta_{K-1}}.\boldsymbol{X_i}}}{1 + \sum_{k=1}^{K-1} e^{\boldsymbol{\beta'_k}.\boldsymbol{X_i}}} \end{aligned} \tag{2.12}$$

The multinomial logistic regression model has an important assumption, which is the independence of irrelevant alternatives. The independence of irrelevant alternatives assumption states that, the odds of preferring one class to another do not depend on the presence or absence of other "irrelevant" alternatives. This condition makes it possible to model the choice of K alternatives as a set of K-1 independent binary choices, in which one alternative is chosen as the base outcome and the other K-1 alternatives are compared against it.

In this study, the dependent variable, Y, for the multinomial logit model has 3 different discrete outcomes as 0, 1 and 2 as 0 corresponding to tranquil period, 1 corresponding to the pre-crisis period and 2 corresponding to the state of being in crisis (may be mentioned adjustment period as well). In such a case, the calculated probabilities for the possible outcomes can be given as follows:

$$\begin{aligned} Pr(Y_{i,t}=0) &= \frac{1}{1+e^{X_{i,t}\beta_1}+e^{X_{i,t}\beta_2}} \\ Pr(Y_{i,t}=1) &= \frac{e^{X_{i,t}\beta_1}}{1+e^{X_{i,t}\beta_1}+e^{X_{i,t}\beta_2}} \\ Pr(Y_{i,t}=2) &= \frac{e^{X_{i,t}\beta_2}}{1+e^{X_{i,t}\beta_1}+e^{X_{i,t}\beta_2}} \end{aligned} \tag{2.13}$$

After constructing the early warning systems for both time windows ('t-1, t, t+1' and 't, t+1, t+2') by using multinomial logistic regression and making the predictions on the data set by using these early warning systems, the first stage of the study gets completed. Then, we move to the second stage in which the aim is to find the ideal threshold level that should be applied on the prediction probabilities to decide whether the economy is in tranquil, pre-crisis or adjustment period. In doing this, it is necessary to take the losses from both Type-1 and Type-2 errors into consideration. For calculating the losses from these Type-1 and Type-2 errors, a loss function has been used in accordance with those used in the previous studies for estimating the total loss arising from wrong signals (or so-called false alarms) and missed crises (Bussiere and Fratzscher, 2008: 111-121). The loss function takes the policy maker's decision into consideration as well. The policy maker's decision, or his choice of the relative cost of missing a crisis, is an important indicator for determining the value of the loss function. The loss function is formulated as follows:

$$L(T) = \theta(prob^{NS/C}(T)) + (1-\theta)(prob^{S}(T)) \tag{2.14}$$

$prob^{NS/C}$: This gives the probability of a missed crisis, it is calculated as the joint probability of the EWS gives the signal of tranquil or adjustment period and a crisis hits.

$prob^{S}$: This gives the probability of signaling for the crisis but the economy not being hit by a crisis, it enters into an adjustment of tranquil period.

θ : It represents the choice of the policy maker's relative cost of missing a crisis, or the policy maker's degree of relative risk aversion

$(1-\theta)$: It represents the choice of policy maker's cost of taking pre-emptive action.

In this loss function, the determinant factor is the action of the policy maker. According to the economic conditions, the policy makers decide which policy has priority compared to others. If the economy has recently been in a contraction period, it may be the sign of a hard time coming. In such a case, the policy maker will accept a deviation from general trend in the economy as a signal for an upcoming crisis. In this condition, the relative risk aversion of the policy maker (θ) will be greater than the policy maker's cost of taking pre-emptive action ($1 - \theta$). If the policy maker trusts in the economy, then he will not consider small deviations from the general trend as problematic situations or a signal for a crisis. So, in this case, the policy maker's cost of taking pre-emptive action ($1 - \theta$) will be greater than the policy maker's relative risk aversion (θ).

In this study, three different values for the relative cost of missing crisis and cost of taking pre-emptive action has been used in a similar way to that of Bussiere and Fratzscher (2008) (Bussiere and Fratzscher, 2008: 111-121) These values are $\theta = 0.2$, $\theta = 0.5$ and $\theta = 0.8$ respectively.

The $\theta = 0.2$ will represent the low theta level for the loss function. The policy maker's relative risk aversion is assumed to be equal to 0.2, which means the policy maker thinks that it is more costly to take pre-emptive action that it is to miss a crisis.

The $\theta = 0.5$ will represent the middle theta level for the loss function. The policy maker's relative risk aversion is equal to 0.5, which means the policy maker thinks that the cost of taking pre-emptive action and the cost of missing a crisis is the same for his economy.

The $\theta = 0.8$ will represent the high theta level for the loss function. The policy maker's relative risk aversion is equal to 0.8, which means the policy maker thinks that the cost of missing a crisis is higher than the cost of taking pre-emptive action for his economy.

Given these definitions, it is expected that, if the policy maker's relative risk aversion is lower ($\theta = 0.2$), he should keep the threshold at a higher level in comparison to a policy maker whose relative risk aversion is higher (i.e. $\theta = 0.8$).

CHAPTER THREE
EMPIRICAL ANALYSIS

The analysis started with 85 exogenous variables. The data set is combined to cover all exogenous indicators, which make variations on the policy implications. Then the variables are divided into the following categories: capital account, debt profile, current account, international variables, financial variables, financial liberalization, real sector variables, institutional variables and fiscal variables. After the variables are grouped depending on their categories, the three best performers are selected from each group. In choosing which variables are more appropriate to be used for crisis prediction, the multinomial logistic regression, which was firstly applied by Bussiere and Fratzscher (2002) to constitute a new approach to predict crisis, was used as an estimation tool (Bussiere and Fratzscher, 2002: 19-47).

The number of variables decreased to 13 in the case of time window 't-1, t, t+1' and to 17 in the case of time windows 't, t+1, t+2' after a series of groupings and selecting the best three performers from all groups. The groupings have been done according to the related literature (Berg and Pattillo, 1999b: 107-138; Bussiere and Fratzscher, 2002: 19-47; Kaminsky et al., 1998: 1-48; Demirguc-Kunt, 1997: 3-17; Manasse et al., 2003: 8-32; Ciarlone and Trebeschi, 2005: 376-395).

In applying this approach, the time interval is divided into three sub periods as a tranquil period, a pre-crisis period and an adjustment period. In the tranquil period, the economy does not have a risk of crisis and the economic variables follow a predictable path. In the pre-crisis period, the economic variables start giving some signals about the coming crisis by deviating from their average path. In the adjustment period, the economy has already been hit by the crisis and measures are being taken for the recovery. Because of this, the economic variables start approaching to their tranquil regime values again and they follow a more predictable path.

This analysis differs from the literature by the fact that it includes 67 countries, which covers both developing and developed countries. Also, the early warning system is constructed using two different time windows as 't-1, t, t+1' and 't, t+1, t+2' and uses multinomial logistic regression as the estimation tool. The system is prepared to catch three types of crises: currency crisis, banking crisis and debt crisis.

In the multinomial logistic regression, the probabilities for a country being in each of the mentioned three different periods is calculated as the following:

$$
\begin{aligned}
Pr(Y_{i,t} = 0) &= \frac{1}{1 + e^{X_{i,t}\beta_1} + e^{X_{i,t}\beta_2}} \\
Pr(Y_{i,t} = 1) &= \frac{e^{X_{i,t}\beta_1}}{1 + e^{X_{i,t}\beta_1} + e^{X_{i,t}\beta_2}} \\
Pr(Y_{i,t} = 2) &= \frac{e^{X_{i,t}\beta_2}}{1 + e^{X_{i,t}\beta_1} + e^{X_{i,t}\beta_2}}
\end{aligned}
\tag{3.1}
$$

When Y is equal to 0, it implies that, the economy is in the tranquil period. If Y is equal to 1, it means that the economy is in the pre-crisis and in the case of Y being equal to 2, the economy is in the adjustment regime.

Here, β_1 and β_2 indicate the marginal impact of a change in the explanatory variables on the probability of being in pre-crisis or adjustment period relative to the probability of being in the tranquil period respectively as shown below:

$$
\begin{aligned}
\frac{Pr(Y_{i,t} = 1)}{Pr(Y_{i,t} = 0)} &= e^{X_{i,t}\beta_1} \\
\frac{Pr(Y_{i,t} = 2)}{Pr(Y_{i,t} = 0)} &= e^{X_{i,t}\beta_2}
\end{aligned}
\tag{3.2}
$$

The multinomial logistic regression consists of three steps and while constructing these steps the methodology of Ciarlone et al was followed (Ciarlone and Trebeschi, 2005: 376-395; Ciarlone and Trebeschi, 2006: 21-24):

- First of all, the multinomial logistic regression was run for each of the 111 variables independently from each other. Although it is a fact that the multinomial logistic regression is meaningful if both the relation between the variables and their deviations are taken into consideration, the aim of this procedure was controlling the Wald statistics and the sign of the coefficient of each variable before beginning the group analysis. This step is helpful for determining the significance and the impact of the variables on the estimation. Indeed, there occurred some problematic cases in choosing the variables for constructing the model. There were some variables (such as fiscal surplus to GDP ratio), which were statistically significant and their predictive powers were very high. However, it has been realized in the final step that those variables would destroy the validity of the constructed model by enlarging its confidence interval and destroying the Wald statistics. As a result, this makes it impossible to construct a set of variables which is suitable to run a multinomial logistic regression to predict crisis by using such variables. Hence, at the end of first stage, that kind of variables were dropped from the data set.

- The second stage includes the grouping of the variables, which come from a similar structure and whose deviations from their trend create similar results on the economy. These variables had already satisfied the requirements of the first stage, which means that they are significant in the 95% confidence interval and they satisfy the Wald statistics. Also they are suitable to form a group to run a multinomial logistic regression on. While grouping the variables, the groups were formed depending on previous studies and data sources (Glick and Hutchison 1999: 6-23; Manasse and Roubini, 2009: 192:205; Laeven and Valencia, 2008: 5-7; Reinhart and Rogoff Online Resources). The variables, which have already been used in previous studies, constituted the first main group, and the variables representing the housing market data constituted the second one. This grouping technique was preferred because the aim was to measure the impact of the housing market data on the prediction power of the early warning system.

- The best performers of each group have been selected according to their significance on the transition from the tranquil to pre-crisis periods. Then, a general multinomial logistic regression has been run over this final group of variables, which successfully have made their way through the previous steps by satisfying the mentioned requirements.

Since both the construction and the results in terms of prediction power are different for the two time windows, 't-1, t, t+1' and 't, t+1, t+2' cases will be analyzed separately in the following sub-sections.

As mentioned earlier, the multinomial logistic regression was run over two different time windows: 't-1, t, t+1' and 't, t+1, t+2'. Both of these windows have different definitions for the cases of tranquil, pre-crisis and adjustment. As a result of this, these two time windows will be analyzed separately in the following sub-sections.

The success of an early warning system is measured by its prediction performance. The aim of this study is to construct an ideal early warning model with the ideal level of threshold to minimize both the number of wrong signals and the number of missing crisis signals. In order to achieve this, the performance of the model is analyzed by sweeping the threshold value for the probabilities from 0.01 to 1. The goodness of fit results for both the in-sample and out-of-sample performances are provided for the threshold levels of 20, 50 and 80 percent. It has to be noted that, the out-of-sample analysis spans the years starting from 2005 going up to 2012.

Table 3: Regime Definition for The Multinomial Logit Model for 't-1, t, t+1'

States of the binomial crisis indicator			Regime in the multinomial
At time t-1	*At time t*	*At time t+1*	*Model at time t*
1	0	0	Tranquil (Y = 0)
0	0	0	
0	0	1	Pre-crisis (Y = 1)
1	1	0	Adjustment (Y = 2)
1	1	1	
0	1	0	
1	0	1	
0	1	1	

3.1 EMPIRICAL RESULTS FOR THE TIME WINDOW 't-1, t, t+1'

As mentioned earlier, a crisis indicator variable has been defined for identifying the years with a crisis. This variable takes the value of 1 for the years with crisis and the value of 0 otherwise. The identification of the state of the economy as either tranquil, pre-crisis or adjustment is done according to the values that the crisis indicator variable takes in a time window of three consecutive years. For the case of 't-1, t, t+1', this window consists of the current year, the year before and the year after it. Given these explanations, there exist eight different combinations of values that the crisis indicator may take in a 3-year window. These combinations and their categorization as either tranquil, pre-crisis or adjustment period are given in Table 3.

As an example, assume that the current year 't' is 2008. If it is known that a country had a crisis in 2008 and 2009. But none in 2007, the crisis indicator variable will take the value of 0, 1 and 1 consecutively for the 3-year time window of 2007-2009. This combination corresponds to the last row of Table 3. Hence, in the data set, the value of the dependent variable Y will become 2 for this given country in year 2008, corresponding to an adjustment period observation. As a result, the crisis indicator variable, which has only two values as 0 and 1, is converted into a categorical variable Y, with three different values 0, 1 and 2. Hence it becomes possible to apply a multinomial logistic regression by using this variable Y as the dependent variable.

As can be seen from the table, the pre-crisis period (Y = 1) is defined by a condition where the economy has not been in a crisis over the last two years but it has an economic problem in the year ahead. The tranquil period (Y = 0) is identified as the case in which the economy either has no crisis in the 3-year period at all, or had only one crisis at time t-1, the year before the current one. The rest of the cases are identified as adjustment periods.

The final multinomial logistic regression includes the following variables with each being given a short abbreviation:

- *ExchRate:* Exchange rates,
- *TrdinServ:* Trade in services (% of GDP),
- *RealIntrRat:* Real interest rate,
- *Inflation:* Inflation (CPI),
- *BnkLiqtoBnkAsst:* Bank liquid reserves to bank asset ratio,
- *DmstcCrdtBnkSec:* Domestic credit provided by banking sector (% of GDP),
- *GDPperCap:* GDP per capita,
- *DegOpen:* Degree of openness to international trade,
- *TotResGrwth:* Total reserve growth,
- *TreaBillRate:* Treasury bill rate,
- *FDItoGDP:* The ratio of FDI to GDP,
- *InfVolatility:* Inflation volatility,
- *RiskPremLend:* Risk premium on lending.

The following table summarizes the final estimation results of the general multinomial logistic regression (Table 4):

Table 4: Results of The Multinomial Logit Regression for 't-1, t, t+1'

Variables	Coeff.	Std. Err.	Z-stat.	95% Conf. Intrvl	
Pre-crisis (Y = 1)					
ExchRate	-0.0736502	0.0349298	-2.11	-0.1421114	-0.005189
TrdinServ	-0.318709	0.1528482	-2.09	-0.6182859	-0.019132
RealIntrRat	-0.1378037	0.2339782	-0.59	-0.5963926	0.3207852
Inflation	0.805995	0.2850855	2.83	0.2472377	1.364752
BnkLiqtoBnkAsst	-59.89469	17.00814	-3.52	-93.23003	-26.55935
DmstcCrdtBnkSec	-0.0405612	0.0252239	-1.61	-0.0899991	0.0088767
GDPperCap	0.0002021	0.0000889	2.27	0.0000277	0.0003764
DegOpen	-5.706173	6.117335	-0.93	-17.69593	6.283583
TotResGrwth	8.563758	2.328971	3.68	3.999058	13.12846

Variables	Coeff.	Std. Err.	Z-stat.	95% Conf. Intrvl	
TreaBillRate	-0.751887	0.3643553	-2.06	-1.46601	-0.0377638
FDItoGDP	66.19929	23.89632	2.77	19.36336	113.0352
InfVolatility	1.196616	1.494313	0.80	-1.732184	4.125416
RiskPremLend	0.6292974	0.2269068	2.77	0.1845683	1.074027
"Const."	0.1951842	4.230678	0.05	-8.096792	8.48716

In the first part of the Table 4, the determinant indicator for the Early warning system is the coefficient part of the analysis, which gives the marginal impact of every component on predicting crisis. The coefficients in the first part of the table represent the estimation result for β_1, which gives information about the likelihood of the economy's entering into a crisis in the following year against the likelihood of its staying in the tranquil period.

This multinomial logistic regression is significant in the 95% confidence interval. In determining the tranquil, pre-crisis and adjustment periods, the threshold value for the probabilities has been swept from 0.01 to 1 to analyze the performance of the model for all threshold values in between. Goodness of fit results will be summarizing the performance for the threshold values of 20, 50 and 80 percent.

According to the estimation results, exogenous indicators, which change from tranquil period to pre-crisis period, are interpreted depending on their odds ratios as follows:

- If there is a decrease in exchange rates, trade in services (% of GDP), real interest rate, domestic credit provided by banking sector (% of GDP) and treasury bill rate; the probability of entering into a crisis increases. It means that, if there is a recovery in the values of these indicators, the economy is entering into the recovery period.

- Inflation, risk premium on lending and GDP per capita behave in the similar way on entering into and exiting from the crisis, as the variations in these variables accelerate entering into the crisis and they are also important in exiting from the crisis.

The following variables make greater impact on entering into and exiting from a crisis than the prior variables:

- The marginal impact of bank liquid reserve to bank asset ratio and degree of openness to international trade is important as, if there is a reduction in these indicators, this will increase the probability of entering into a crisis and if there is a rise in them, this will ease existing from the crisis.

- Inflation volatility, FDI to GDP ratio and total reserve growth (%) make similar effects in determining the probability of entering into and existing from the crisis. It seems that they both have positive marginal effects on the probability of entering into a crisis. A fall in any of these values shows that the economy is entering into a recovery period.

3.1.1 Predictive Ability for Time Window 't-1, t, t+1'

If accurate and harmonious variables are chosen and used in the estimation, crisis prediction becomes an easy work but the success of predicting crisis determine the contribution of the work into the literature

The success of a crisis prediction depends on different factors. Defining a threshold level is the determining factor of which cases are to be identified as crisis and which are not. Then, it is expected from the crisis prediction mechanism to give signal for the cases of crisis, probabilities of which are above the defined threshold level. Choosing a correct threshold level is very critical.

If a lower threshold is chosen, the more signals the model will send, but will have the drawback of also increasing the number of wrong signals or so called false alarms (Type-2 errors). In contrast, increasing the threshold level reduces the number of wrong signals at the expense of increasing the number of missed crises (Type-1 errors) (Bussiere and Fratzscher, 2006: 953-973).

This fact constitutes the main motivation of this study, which is to find an answer to how to minimize both Type-1 and Type-2 errors in predicting crisis. So, for both types of time windows, all threshold level are analyzed and 3 of them chosen in the similar way to that of literature (Bussiere and Fratzscher, 2008: 111-121). As a result of this, goodness of fit results for both in-sample and out-of-sample are evaluated at the threshold levels of 20, 50 and 80 percent. Again it has to be noted that, the out-of-sample analysis has been carried out on the data between years 2005 and 2012.

The in-sample and out-of-sample performance analysis of time window of "t-1, t, t+1" hold for the model consisting of the following variables: Exchange rates, trade in services (% of GDP), real interest rate, inflation (CPI), bank liquid reserve to bank asset ratio, domestic credit provided by banking sector (% of GDP), GDP per capita, degree of openness to international trade, total reserve growth (%), treasury bill rate, FDI to GDP, inflation volatility, risk premium on lending.

The in-sample and out-of-sample performances of this early warning system, consisting of these mentioned variables, are given in the following table:

According to the performance results the prediction power of the model is reliable enough to make credible interpretation about the future of the economy when it is com-

Table 5: Performance of The Model for Various Threshold Levels, 't-1, t, t+1'

	In Sample	*Out of Sample*
Goodness of fit (20% cut off)		
Percent of crisis periods correctly called (Y=1)	60	71
False alarms as percent of total alarms	30	25
Percent of tranquil periods correctly called (Y=0)	99	99
Percent of adjustment period correctly called (Y=2)	54	62
Goodness of fit (50% cut off)		
Percent of crisis periods correctly called (Y=1)	60	71
False alarms as percent of total alarms	0	0
Percent of tranquil periods correctly called (Y=0)	96	95
Percent of adjustment period correctly called (Y=2)	25	38
Goodness of fit (80% cut off)		
Percent of crisis periods correctly called (Y=1)	30	43
False alarms as percent of total alarms	0	0
Percent of tranquil periods correctly called (Y=0)	89	87
Percent of adjustment period correctly called (Y=2)	4	8

pared to the related literature (Ciarlone and Trebeschi, 2005: 376-395). The estimation results prove its stability since, as the threshold level increases, percent of correctly called crises increases and percentage ratio of false alarms to total alarms decreases. Similar patterns occur for the percentages of correctly called tranquil and adjustment periods, as the percentage of correctly called cases increases with an increased threshold level. These results allow us to move to the second stage of the analysis: loss function for an ideal early warning system for time window of 't-1, t, t+1'.

3.2 EMPIRICAL RESULTS FOR THE TIME WINDOW 't, t+1, t+2'

For the case of 't-1, t, t+1', the identification of the state of the economy as either tranquil, pre-crisis or adjustment is again done according to the values that the crisis indicator variable takes in a time window of three consecutive years. However, for this case, the time window consists of the current year and consecutive 2 years following the current one. Again there exist eight different combinations of values that the crisis indicator may take in a 3-year window. These combinations and their categorization as either tranquil, pre-crisis or adjustment period are given in Table 6.

Same as the previous one, tranquil period is denoted by $Y = 0$, pre-crisis is denoted by $Y = 1$ and the adjustment period is denoted by $Y = 2$. The cases corresponding to each

Table 6: Regime Definition for The Multinomial Logit Model for 't, t+1, t+2'

States of the binomial crisis indicator			Regime in the multinomial
At time t	*At time t+1*	*At time t+2*	*Model at time t*
0	0	0	Tranquil (Y = 0)
1	0	0	
0	0	1	Pre-crisis (Y = 1)
0	1	0	
0	1	1	
1	1	0	Adjustment (Y = 2)
1	1	1	
1	0	1	

period is given as follows: The cases in which there is no crisis in any of the three years, or there is a crisis at time t, but no crises in t+1 and t+2 are considered as 'tranquil periods'. The cases in which there is no crisis at time t, but there exists a crisis either in t+1 or t+2 or both are considered as periods of 'pre-crisis'. The rest of the eight combinations are considered as adjustment or recovery periods, which means that a crisis has already hit the economy and the necessary adjustments are being done. The multinomial logistic model is forecasted by assuming the tranquil period as the benchmark (the base outcome).

For this time window, the final regression for the model is constructed by 17 macroeconomic and financial variables. The entire sample set includes the period from 1980 to 2012. The final regression has been run over 183 observations. It satisfies the 95% confidence interval. The model's in-sample and out-of-sample performances (as out-of-sample performance covering the years between 2005 and 2012) are controlled for all threshold levels and the estimation result of the model at the threshold values of 20, 50 and 80 percent are given as a summary for its performance.

The final multinomial logistic regression includes the following variables with each being given a short abbreviation:

- *IntResGrwth:* International reserve growth,
- *CurrAccGDP:* The ratio of current account to GDP,
- *TotResGrwth:* Total reserve growth,
- *FDItoGDP:* The ratio of FDI to GDP,
- *ChngTrd:* Change in terms of trade,
- *DmstcCrdttoPrvtSec:* Domestic credit to private sector (% of GDP),

- *DmstcCrdtBnkSec:* Domestic credit provided by banking sector (% of GDP),
- *RealDmstcCrdtGrwth:* Real domestic credit growth,
- *ImprtGrwth:* Import growth rate,
- *DegOpen:* Degree of openness,
- *ExprtGrwth:* Export growth rate,
- *SPGlobEqInd:* S&P global equity indices (annual % change),
- *TaxRev:* Tax revenue (% of GDP),
- *BnkCaptoAsstRat:* Bank capital to asset ratio,
- *IntrRatGovSec:* Interest rates of government securities & government bonds,
- *BnkLiqtoBnkAsst:* Bank liquid reserves to bank asset ratio,
- *GovTotDbt:* Central government total debt (% of GDP),

Table 7 summarizes the final estimation results of the general multinomial logistic regression:

Table 7: Results of The Multinomial Logit Regression for 't, t+1, t+2'

Variables	Coeff.	Std. Err.	Z-stat.	95% Conf. Intrvl	
Pre-crisis (Y = 1)					
IntResGrwth	-2.730437	2.464859	-1.11	-7.561473	2.100599
CurrAccGDP	-19.54476	7.86081	-2.49	-34.95166	-4.137852
TotResGrwth	7.015116	3.456021	2.03	0.2414407	13.78879
FDItoGDP	0.6756377	0.6978827	0.97	-0.6921872	2.043463
ChngTrd	10.26979	7.799876	1.32	-5.017689	25.55726
DmstcCrdttoPrvtSec	-0.0882303	0.0486254	-1.81	-0.1835344	0.0070737
DmstcCrdtBnkSec	0.0947688	0.0450959	2.10	0.0063825	0.183155
RealDmstcCrdtGrwth	-1.467255	4.583532	-0.32	-10.45081	7.516301
ImprtGrwth	8.25583	6.743335	1.22	-4.960864	21.47252
DegOpen	-0.5717135	1.491226	-0.38	-3.494464	2.351037
ExprtGrwth	-5.33439	7.095732	-0.75	-19.24177	8.57299
SPGlobEqInd	0.0527994	0.0147673	3.58	0.0238561	0.0817428
TaxRev	0.2211346	0.0958674	2.31	0.033238	0.4090312
BnkCaptoAsstRat	-0.4087485	0.2331953	-1.75	-0.865803	0.0483059
IntrRatGovSec	-0.3289624	0.4689483	-0.70	-1.248084	0.5901594
BnkLiqtoBnkAsst	-86.23896	23.12011	-3.73	-131.5535	-40.92438
GovTotDbt	-0.0194944	0.0204439	-0.95	-0.0595638	0.020575
"Const."	-2.341122	3.384369	-0.69	-8.974362	4.292119

This multinomial logistic regression is significant in the 95% confidence interval. In determining the tranquil, pre-crisis and adjustment periods, the threshold value for the probabilities has been swept from 0.01 to 1 to analyze the performance of the model for all threshold values in between. Goodness of fit results will be summarizing the performance for the threshold values of 20, 50 and 80 percent.

According to the estimation results, exogenous indicators, which changes from tranquil period to pre-crisis period, are interpreted depending on their odds ratios as follows:

- In the case of a fall in the international reserve growth, domestic credit to private sector (% of GDP), real domestic credit growth, degree of openness to international trade, export growth rate, bank capital to asset ratio (%), interest rate of government securities and bonds and central government debt as percentage of GDP; the probability of entering into the crisis increases. It means that, if there is a recovery in the value of these variables, the economy is entering into the recovery period.

- If there is a rise in the value of FDI to GDP, Domestic credit provided by banking sector (% of GDP), S&P Global Equity Indices and tax revenue, it signals that the economy gives the signal of entering into crisis. These indicators behave in a similar pattern on exiting from crisis.

The following variables make greater impact on entering into a crisis and exiting from a crisis than the prior variables.

- The marginal impact of current account to GDP and bank liquid reserve to bank asset ratio is important as, if there is a decrease in these indicators, this will increase the probability of entering into a crisis and if there is a rise in them, this will ease exiting from the crisis.

- Total reserve growth, import growth and change in terms of trade make similar effects on entering into and exiting from the crisis. It seems that they both have positive marginal effects on the probability of entering into a crisis. A fall in these values show that the economy is entering into a recovery period.

3.2.1 Predictive Ability for Time Window 't, t+1, t+2'

For this time window, again all threshold levels are analyzed (the threshold level has been swept from 0.01 to 1) and the goodness of fit results for both in-sample and out-of-sample performances are evaluated at the threshold levels of 20, 50 and 80 percent.

The in-sample and out-of-sample performance analysis of time window of "t, t+1, t+2" hold for the model consisting of the following variables: International reserve growth, current account to GDP, total reserve growth (%), FDI to GDP, Change in terms of trade, Domestic credit to private sector (% of GDP), real domestic credit growth, import growth, degree of openness to international trade, export growth rate, S&P Global Equity Indices, Tax revenue (% of GDP), Bank capital to asset ratio (%), Interest rate of government securities and bonds, Bank liquid reserve to bank asset ratio, Central government debt as percentage of GDP.

The in-sample and out-of-sample performance of this early warning system, consisting of these mentioned variables, is given following table:

Table 8: Performance of The Model for Various Threshold Levels, 't, t+1, t+2'

	In Sample	*Out of Sample*
Goodness of fit (20% cut off)		
Percent of crisis periods correctly called (Y=1)	92	92
False alarms as percent of total alarms	38	52
Percent of tranquil periods correctly called (Y=0)	98	96
Percent of adjustment period correctly called (Y=2)	93	92
Goodness of fit (50% cut off)		
Percent of crisis periods correctly called (Y=1)	68	75
False alarms as percent of total alarms	13	15
Percent of tranquil periods correctly called (Y=0)	89	89
Percent of adjustment period correctly called (Y=2)	78	77
Goodness of fit (80% cut off)		
Percent of crisis periods correctly called (Y=1)	32	33
False alarms as percent of total alarms	1	4
Percent of tranquil periods correctly called (Y=0)	71	65
Percent of adjustment period correctly called (Y=2)	63	62

According to the performance results the prediction power of the model is reliable enough to make credible interpretation about the future of the economy when it is compared to the related literature (Bussiere and Fratzscher, 2006: 953-973). The estimation results prove its stability since, as the threshold level increases, percent of correctly called crises increases and percentage ratio of false alarms to total alarms decreases. Similar patterns occur for the percentages of correctly called tranquil and adjustment periods, as the percentage of correctly called cases increases with an increased threshold level. These results allow us to move to the second stage of the analysis: loss function for an ideal early warning system for time window of 't, t+1, t+2'.

3.3 CONSTRUCTION OF THE OPTIMAL EWS FOR TIME WINDOW 't-1, t, t+1'

As mentioned earlier, the aim of this study is to find an optimum threshold level for different time windows to minimize the loss of the policy makers due to wrong signals and missing crisis. In the first stage of the study, early warning systems have been constructed for two different time windows with reliable predictive powers allowing testing the effect of different threshold levels on the performance and their impact on the policy.

Now, as the second stage, the aim is to achieve the optimal EWS to minimize the loss of the policy maker. In order to find the optimum threshold level, the estimation on the model given in Section 3.1, which was generated by running multinomial logistic regression over the time window of 't-1, t, t+1', has been re-run by sweeping the threshold values from 0.01 to 1 in accordance with the prior studies in the literature (Bussiere and Fratzscher, 2008: 111-121).

Although the aim of early warning systems is to keep the economy safe from crises, sometimes, unexpected results occur. The case in which the economy enters into a contraction period, but not a crisis is an example of this: If the early warning system's signal level is low (it means that the threshold level is low and in our case the threshold level of 20% represents this situation) it will signal the situation as a crisis. Hence, although the economy has a normal period in its cycle, when the policy makers accept this situation as a crisis, he will take pre-emptive decisions. This will create an additional cost for the economy. These types of wrong decisions are named as Type-1 errors for early warning systems. In this type of error, the cost of false alarms will be problem for the policy makers, but the number of missing crisis is lower than that for the higher threshold levels.

The second case corresponds to the converse situation. The policy maker ignores the coming crisis and he accepts the problematic situation as a temporary deviation (it means that the threshold level is high, which in our case corresponds to the 80% threshold). The early warning system does not signal for the coming crisis and the policy makers do not take the necessary pre-emptive decisions to prevent crisis. Although the economy will have a crisis in the near future, the government does not take this situation into consideration. Under these circumstances, the early warning system will miss the crisis and the economy will have to pay the cost of missing crisis. These types of wrong decisions are named as Type-2 errors for the early warning systems. In this type of error, the cost of missing a crisis will be problem for the policy makers, but the number of false alarms is lower than that for the lower threshold levels.

Hence, the complicated problem of making a preference between these two types of errors occurs. The trade-off arises between the number of false alarms and the number of missed crisis. If the threshold level increases it will create two outcomes: the number of false alarms will decrease but the number of missed crises will increase. On the other hand, if the threshold level decreases it will create two outcomes: the number of false alarms will increase but the number of missed crises will decrease. The policy maker's objective function is the most important determinant factor for the choice of the threshold level.

In this study, it is assumed that taking pre-emptive decisions and missing a crisis both have a cost for the policy maker. So he aims to minimize the unnecessary costs, which arise because of these two cases. This study uses a loss function to calculate the whole loss of the policy maker as a result of these two cases. The literature that is presented by Bussiere and Fratzscher (2008) to formulate this function is followed in this study:

$$L(T) = \theta(prob^{NS/C}(T)) + (1-\theta)(prob^{S}(T)) \tag{3.3}$$

$prob^{NS/C}$: This gives the probability of a missed crisis, it is calculated as the joint probability of the EWS gives the signal of tranquil or adjustment period and a crisis hits.

$prob^{S}$: This gives the probability of signaling for the crisis but the economy not being hit by a crisis, it enters into an adjustment of tranquil period.

θ : It represents the choice of the policy maker's relative cost of missing a crisis, or the policy maker's degree of relative risk aversion

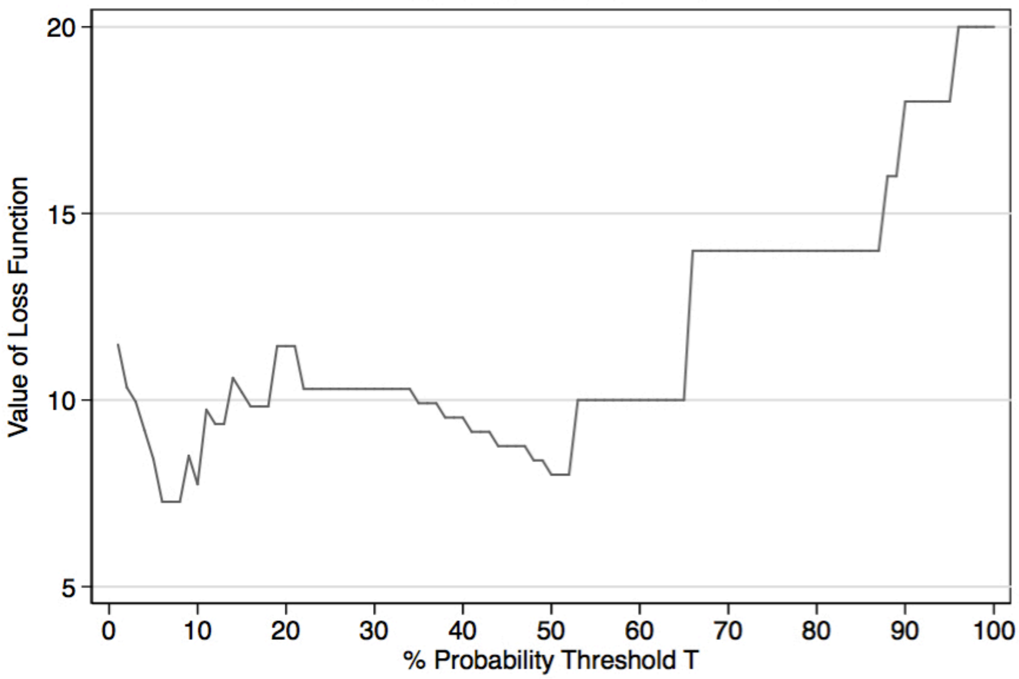
$(1-\theta)$: It represents the choice of policy maker's cost of taking pre-emptive action.

According to this loss function, the choice of the policy maker is the determinant factor for choosing an optimal threshold level. The policy maker will choose his relative cost of missing a crisis and cost of taking pre-emptive action, and depending on his choice the optimal threshold level will appear. In this study, three different values for the relative cost of missing crisis and cost of taking pre-emptive action has been used in a similar way to that of Bussiere and Fratzscher (2008) (Bussiere and Fratzscher, 2008: 111-121). These values are $\theta = 0.2$, $\theta = 0.5$ and $\theta = 0.8$ respectively.

- Given this loss function, the optimal threshold level, which minimizes the value of loss function, is determined by θ. In the case of $\theta = 0.2$, the value of loss function takes its lowest value at the threshold level of 8%. This implies that, if the policy maker uses 't-1, t, t+1' time window for model construction and prediction and the policy maker's degree of relative risk aversion (θ) is equal to 0.2; multinomial logistic regression model provides the best trade off between missing crisis and giving wrong signals at the threshold level of 8%.

- In the case of $\theta = 0.5$, the value of loss function takes its lowest value at the threshold level of 7%. It means that, if the decision maker utilizes the multinomial logistic

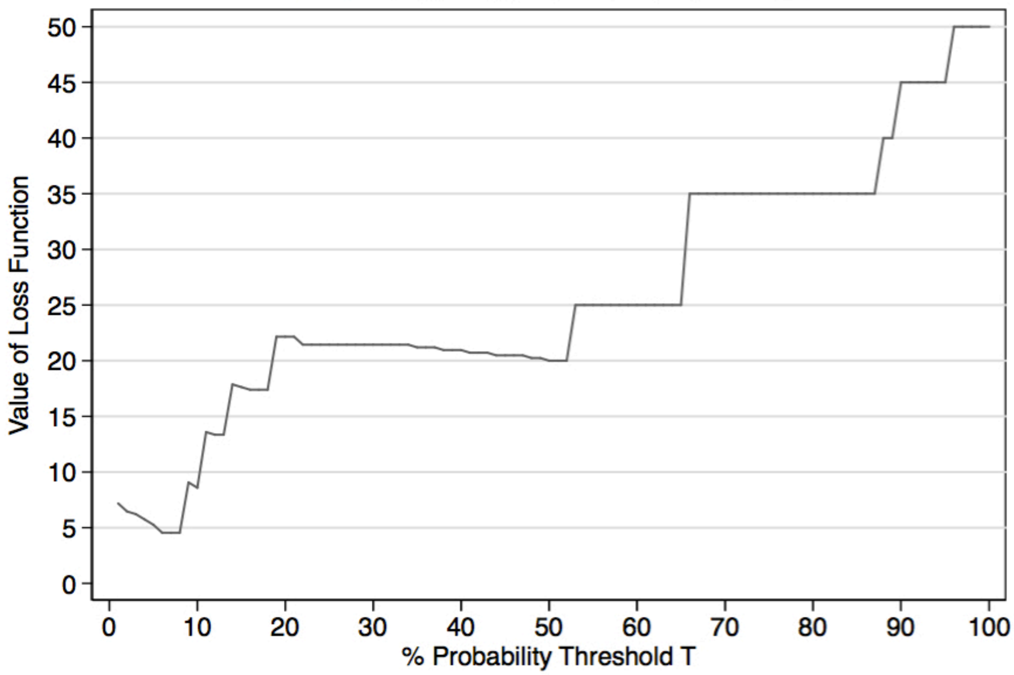
Figure 1: Loss Function for Time Window 't-1, t, t+1' and $\theta = 0.2$



regression model using the time window of 't-1, t, t+1' to design its early warning system and the policy maker's degree of relative risk aversion (θ) is equal to 0.5; multinomial logistic regression model provides the best trade off between missing crisis and giving wrong signals at the threshold level of 7%.

- As shown in Figure 3, if $\theta = 0.8$, the value of loss function takes its lowest value at the threshold level of 6%. It means that, if the decision maker uses 't-1, t, t+1' time window to construct the early warning system and the policy maker's degree of relative risk aversion (θ) is equal to 0.8; multinomial logistic regression model gives the best trade off between missing crisis and giving wrong signal at the threshold level of 6%.

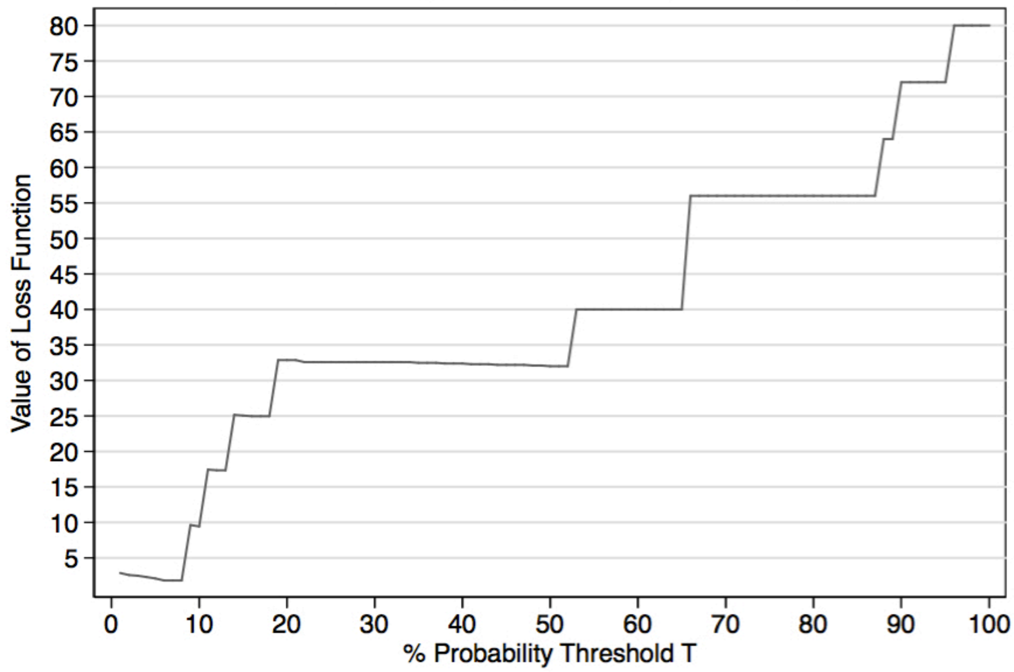
Figure 2: Loss Function for Time window 't-1, t, t+1' and $\theta = 0.5$



When the values of the loss functions for the time window of 't-1, t, t+1' are compared, the policy maker's degree of relative risk aversion (θ) being 0.8 and threshold level of 6% gives the minimum value for best trade off between missing crisis and giving wrong signal.

This early warning system analyzed 67 countries, which include both developing and developed ones. It spans the years between 1980 and 2012. The multinomial logistic regression is used for predicting crisis and the time window used is 't-1, t, t+1'. The multinomial logistic regression is estimated for all possible degrees of risk aversion (θ), and for all possible threshold levels. In accordance with the results of the predictions, following results can be obtained: If the policy maker's degree of relative risk aversion (the relative cost of missing a crisis, θ) is lower than the cost of taking pre-emptive action ($1 - \theta$); the policy maker should prefer higher threshold levels than lower threshold levels. If the policy maker's degree of relative risk aversion (the relative cost of missing a crisis, θ) is higher than the cost of taking pre-emptive action ($1 - \theta$); the policy maker should prefer lower threshold levels than higher threshold levels. As the policy maker's relative risk aversion (the relative cost of missing a crisis) increases, the optimum threshold value, which minimizes the loss function, decreases. In this study, for all threshold levels and relative risk

Figure 3: Loss Function for Time Window 't-1, t, t+1' and $\theta = 0.8$



aversions; the loss function takes its minimum value at the relative risk aversion of 0.8 and at the threshold level of 6%.

The results suited to the theory of the early warning system. According to the theory, if the policy maker's relative cost of missing a crisis (the policy maker's degree of relative risk aversion) is high, he will give priority to preventing crisis. It means that, he will accept all types of signals, as a crisis signal. It means that, he will keep the threshold lower, as his relative cost of missing a crisis (the policy maker's degree of relative risk aversion) increases. To summarize, according to the theory if the policy maker's (θ) increases, he will decrease the threshold level of the early warning system.

In this part of the research, for the time window of 't-1, t, t+1'; if the policy maker's relative risk aversion is equal to 0.8, the optimum threshold level is equal to 6%. In the case of the policy maker's relative risk aversion is equal to 0.5, the optimum threshold level is equal to 7% and if the policy maker's relative risk aversion is equal to 0.2, the optimum threshold level is equal to 8%. As it is seen from the result, when the policy maker gives priority to the cost of missing a crisis, he will increase his relative risk aversion and decrease the threshold level to catch all crises, before they hit the economy. But if he gives priority to the cost of taking pre-emptive action, he will decrease his relative risk aversion and increase threshold level to not to consider all types of signals as a crisis indicator.

For all relative risk aversion values and threshold levels, the model gives the minimum value of the loss function in the case of policy maker's degree of relative risk aversion (θ) equal to 0.8 and threshold level of 6%, and that gives the minimum value for the best trade off between missing crisis and giving wrong signal. It shows that, the cost of missing a crisis is greater than cost of taking pre-emptive action for this model.

3.4 CONSTRUCTION OF THE OPTIMAL EWS FOR TIME WINDOW 't, t+1, t+2'

In this part of the study, the procedure described in Section 3.3 will be applied on the early warning system developed by applying multinomial logistic regression over the time window of 't, t+1, t+2'. In finding the optimum threshold level for this time window, the prediction results of the early warning system described in Section 3.2 will be used. Again it has been proven that the predictive power of the model is reliable enough to make testing the effect of different threshold levels on the performance and their impact on the policy possible.

The estimation on the EWS model described in Section 3.2 has been re-run by sweeping the threshold values from 0.01 to 1 in accordance with the prior studies in the literature (Bussiere and Fratzscher, 2008: 111-121).

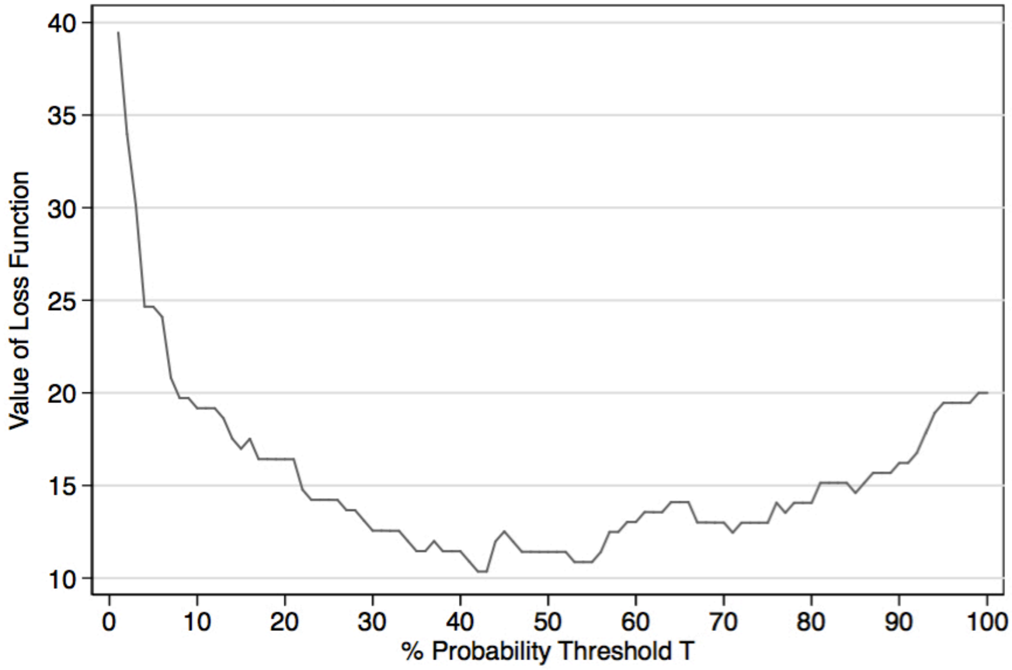
As described in Section 3.3, it is again assumed that taking pre-emptive decision and missing a crisis both have a cost for the policy maker. As a result of this, his target is to minimize the unnecessary costs, which arise because of these two cases. The same loss function formulas given in Equation 3.3 have been used but now the time window has been changed to 't, t+1, t+2'.

As done in Section 3.3, for time window of 't-1, t, t+1', three different values for the relative cost of missing crisis and cost of taking pre-emptive action has been used These values are $\theta = 0.2$, $\theta = 0.5$ and $\theta = 0.8$ respectively.

- Given this loss function in Figure 4, the optimal threshold level, which minimizes the value of loss function, is determined by θ. In the case of $\theta = 0.2$, the value of loss function takes its lowest value at the threshold level of 55%. This implies that, if the policy maker uses 't-1, t, t+1' time window for model construction and prediction and the policy maker's degree of relative risk aversion (θ) is equal to 0.2; multinomial logistic regression model provides the best trade-off between missing crisis and giving wrong signals at the threshold level of 55%.

- In the case of $\theta = 0.5$, which is shown in Figure 5; the value of loss function takes its lowest value at the threshold level of 23%. It means that, if the decision maker utilizes

Figure 4: Loss Function for Time Window 't, t+1, t+2' and $\theta = 0.2$



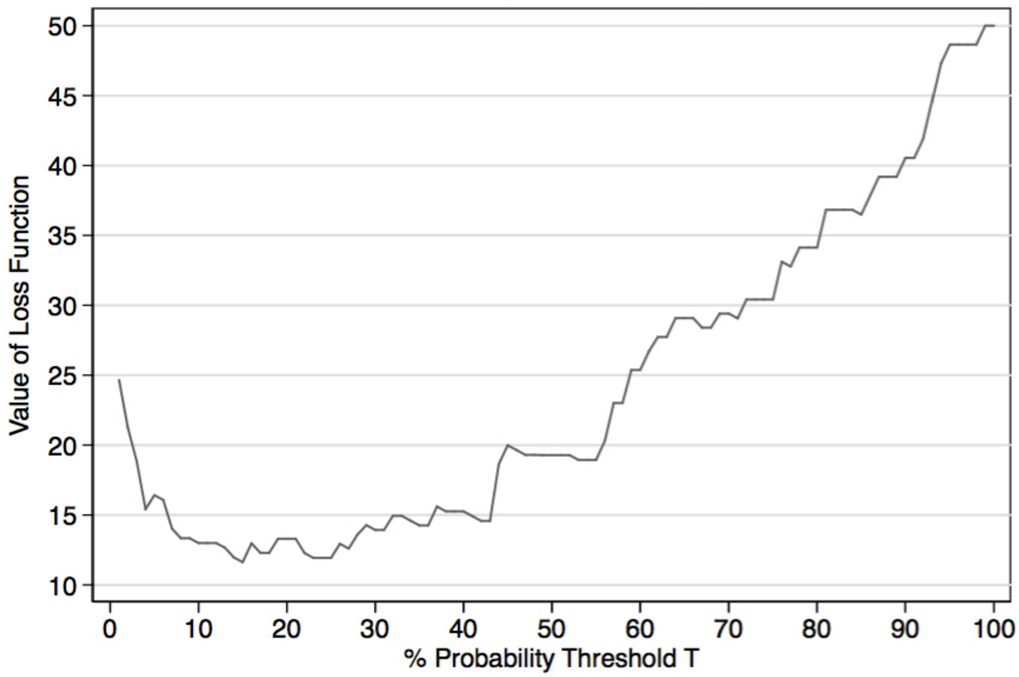
the multinomial logistic regression model using the time window of 't, t+1, t+2' to design its early warning system and the policy maker's degree of relative risk aversion (θ) is equal to 0.5; multinomial logistic regression model provides the best trade-off between missing crisis and giving wrong signals at the threshold level of 23%.

- If $\theta = 0.8$, the value of loss function takes its lowest value at the threshold level of 4%. It means that, if the decision maker uses 't, t+1, t+2' time window to construct the early warning system and the policy maker's degree of relative risk aversion (θ) is equal to 0.8; multinomial logistic regression model gives the best trade-off between missing crisis and giving wrong signal at the threshold level of 4%.

When the values of the loss functions for the time window of 't, t+1, t+2' are compared, the policy maker's degree of relative risk aversion (θ) being 0.8 and threshold level of 4% gives the minimum value for best trade-off between missing crisis and giving wrong signal.

This early warning system analyzed 67 countries, which include both developing and developed ones. It spans the years between 1980 and 2012. The multinomial logistic regression is used for predicting crisis and the time window used is 't, t+1, t+2'. The multinomial logistic regression is estimated for all possible degrees of risk aversion (θ), and for all possible threshold levels.

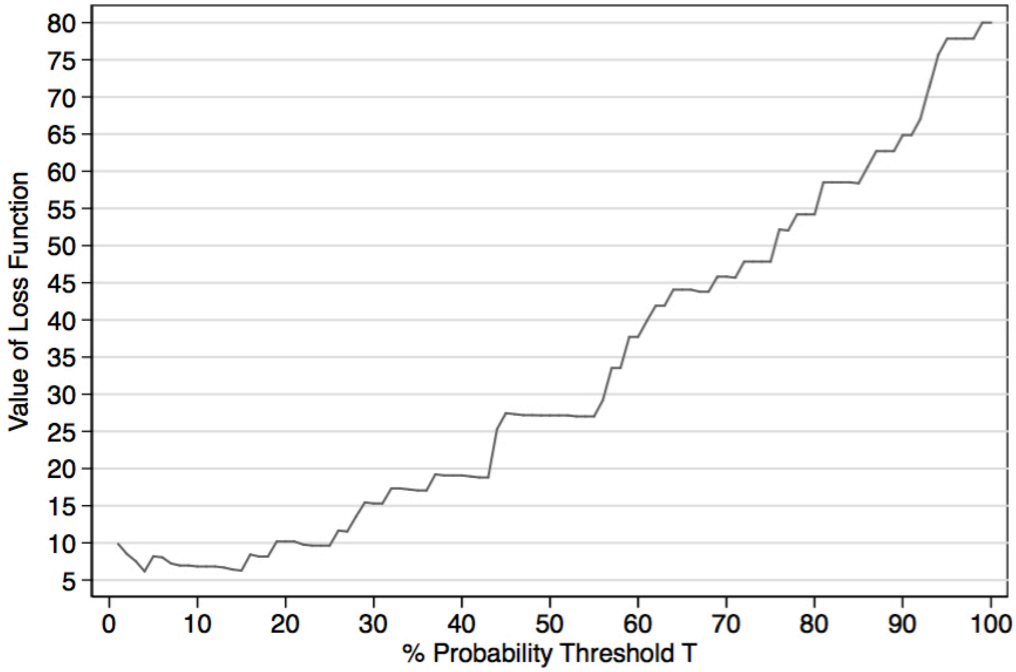
Figure 5: Loss Function for Time Window 't, t+1, t+2' and $\theta = 0.5$



In accordance with the results of the predictions, following results can be obtained: If the policy maker's degree of relative risk aversion (the relative cost of missing a crisis, θ) is lower than the cost of taking pre-emptive action $(1-\theta)$; the policy maker should prefer higher threshold levels than lower threshold levels. If the policy maker's degree of relative risk aversion (the relative cost of missing a crisis, θ) is higher than the cost of taking pre-emptive action $(1-\theta)$; the policy maker should prefer lower threshold levels than higher threshold levels. As the policy maker's relative risk aversion (the relative cost of missing a crisis) increases, the optimum threshold value, which minimizes the loss function, decreases. In this study, for all threshold levels and relative risk aversions; the loss function takes its minimum value at the relative risk aversion of 0.8 and at the threshold level of 4%.

The results suited to the theory of the early warning system. According to the theory, if the policy maker's relative cost of missing a crisis (the policy maker's degree of relative risk aversion) is high, he will give priority to preventing crisis. It means that, he will accept all types of signals, as a crisis signal. It means that, he will keep the threshold lower, as his relative cost of missing a crisis (the policy maker's degree of relative risk aversion) increases. To summarize, according to the theory if the policy maker's (θ) increases, he will decrease the threshold level of the early warning system.

Figure 6: Loss Function for Time Window 't, t+1, t+2' and $\theta = 0.8$



In this part of the research, for the time window of 't, t+1, t+2'; if the policy maker's relative risk aversion is equal to 0.8, the optimum threshold level is equal to 4%. In the case of the policy maker's relative risk aversion is equal to 0.5, the optimum threshold level is equal to 23% and if the policy maker's relative risk aversion is equal to 0.2, the optimum threshold level is equal to 55%. As it is seen from the result, when the policy maker gives priority to the cost of missing a crisis, he will increase his relative risk aversion and decrease the threshold level to catch all crises, before they hit the economy. But if he gives priority to the cost of taking pre-emptive action, he will decrease his relative risk aversion and increase threshold level to not to consider all types of signals as a crisis indicator.

For all relative risk aversion values and threshold levels, the model gives the minimum value of the loss function in the case of policy maker's degree of relative risk aversion (θ) equal to 0.8 and threshold level of 4%, and that gives the minimum value for the best trade off between missing crisis and giving wrong signal. It shows that, the cost of missing a crisis is greater than cost of taking pre-emptive action for this model.

CONCLUSION

"This thesis aims to find an ideal early warning system, whose target is to protect the countries from the loss originating from both a missed crisis and taking unnecessary precautions for a false alarm. To achieve this aim, first of all it constructs early warning systems and then the prediction results from these early warning systems are used to find the optimal early warning system to minimize the loss by the help of a loss function.

The literature on the early warning systems generally pays more attention to the cost of missing a crisis (Bussiere and Fratzscher, 2002: 19-47), so they ignore the cost of taking pre-emptive actions for a false alarm. But in the following studies, the literature starts making research on both types of costs. There are a few studies, which work on the probabilistic significance of the early warning systems. However, none of them uses the multinomial logistic regression for two different time windows for predicting currency, banking and debt crisis together. This study also differentiates from similar studies with its comprehensive data set, which includes 67 countries and spans the years between 1980 and 2012.

The data used in both early warning systems are taken form the World Bank, IMF, OECD. The data set consists of variables both those used in the previous studies and also new additional variables, which are added to capture all the variations in the economy. The estimation started with 85 exogenous variables. They were divided into groups according to the similarity of their effects on the economy, and then the best performers of each group have been selected to constitute the final multinomial logistic regression data set. Since there are two different time windows that affect the criteria of choosing appropriate variables, the selected variables for the final data set are different for these two different time windows.

The findings in this study indicate that, for both types of time windows, the policy maker's loss function takes the minimum value when more importance is given to the cost of missing a crisis. As a consequence of this, the threshold level should be kept at the lowest level to stay on the toes and minimize the risk of missing an upcoming crisis. The results show that, for the time window of 't-1, t, t+1', the system correctly predicts 60% of the crisis periods with the threshold level of 20%. Again with the same threshold level, the system's out of sample performance in predicting crisis periods is equal to 71%. Also the system sends false alarms for the 30% of the non-crisis periods for the in sample performance with the threshold level of 20% and this ratio drops to 25% for its out of sample performance. For the time window of 't, t+1, t+2', the system correctly catches 92% of the crisis periods with the threshold level of 20% and the system's out of sample performance is at the same level, 92%, in predicting crisis periods for the threshold level of 20%. At the threshold level of 20; the system sends false alarms for the 38% percent of the non-crisis periods for the in sample performance and its ratio of false alarms at the same threshold level for the out of sample performance is equal to 52%.

For constructing an ideal early warning system, a loss function is constructed to minimize the costs of missing a crisis (the relative risk aversion) and taking pre-emptive action for a false alarm, by using the results of two early warning systems for two different time windows. In this loss function, the decision of the policy maker represents the exogenous indicators, which show the preference of the policy maker between the cost of taking pre-emptive action and the cost of missing a crisis. In the loss function, the amount of loss is determined by the threshold level (T), which defines the characteristics of the signal and classifies it as either a crisis, a tranquil or an adjustment signal. The second indicator factor is the decision of the policy maker, θ, which represents the choice of the policy maker's relative cost of missing a crisis. The loss function is calculated by sweeping the threshold value from 0.01 to 1 to cover all different threshold levels, and 3 different values of θ are used for analysis as $\theta = 0.2$ representing the case in which the relative cost of missing a crisis is chosen to be lower than that of taking pre-emptive actions for a false alarm, $\theta = 0.8$ representing the reverse, and $\theta = 0.5$ representing the case of both costs chosen to be equal. The whole analysis is repeated for both time windows.

The loss functions for both time windows take the lowest value at the policy maker's relative risk aversion being equal to 0.8. For the time window, 't-1, t, t+1' the lowest value occurs at the threshold level of 6% together with $\theta = 0.8$ whereas, the minimum for the loss function is obtained with the threshold level of 4% for the time window of 't, t+1, t+2'. These results lead to a general interpretation as follows: For all types of countries (it is possible to generalize this result to all countries, since the country set includes both developing and developed countries), for both types of the early warning systems with two different time windows; the policy makers should give priority to the cost of missing a crisis rather than to the cost of taking pre-emptive actions for a false alarm, to minimize the amount of loss originating from the errors in crisis prediction. Hence, a lower threshold level should be preferred to minimize the risk of missing a crisis by interpreting most of the deviations in the economy from the normal trend as a signal for an upcoming crisis. Consequently, the highest relative risk aversion (θ) and a lowest threshold level (T) as a combination gives the lowest values for the loss function.

If the amounts of losses in both time windows are compared for the case of $\theta = 0.8$, the value of the loss for time window 't, t+1, t+2' is equal to 6.16 and the value of loss for time window 't-1, t, t+1' is equal to 1.81. According to these results, by using the time window of 't-1, t, t+1' the loss function attains its lowest value for the studied data set. Hence, it is deduced that a policy maker should run the multinomial logistic regression to construct the model on the time window of 't-1, t, t+1' to minimize the value of the loss function.

This study differs from the prior studies from many perspectives. The multinomial logistic regression model, which is used to predict crisis, is constructed to predict not only one, but all types of crisis as currency, banking and debt crisis. Its data set includes a large data collection; by this way the study takes many kinds of indicators into consideration and finds the most effective ones in predicting crisis. Moreover, the analysis part of this estimation consists of two different time windows and new definitions are provided for the pre-crisis, tranquil and adjustment periods. By this way, the crisis prediction power is aimed to be increased. Also, the trade-off between costs of missing a crisis and the cost of taking pre-emptive action is analyzed for a large data set spanning the years between 1980 and 2012.

The findings of this study will help both researchers and the policy makers in constructing the optimal early warning systems to resolve the trade-off problems, which arise in predictions done by using these systems.

As a future work, the data set might be divided into two main categories for the countries as developing and the developed countries and the estimations might be repeated for each set to investigate the differences between the policies to be applied in developing countries and developed countries in order to both improve the prediction powers of the early warning systems and minimize the loss.

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