Early Warning Systems for Economic Crises in South Africa

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Abstract:

This paper develops a series of Early Warning System models for debt crises. This paper uses a Debt Pressure index to define crisis periods and then demonstrates how one can go about trying to forecast these periods using Logit and Markov-switching Models. An alternative approach, whereby ordinary least squares (OLS) is used to create Early Warning System models, is introduced. A graphical analysis is also conducted. Three useful Early Warning System models emerge from this study.

1. Introduction

Although economists had long been studying crises with the advantage of hindsight, it was after the Tequila Crisis in 1994-5 that economists focused their attention towards crisis *prediction*. Such a topic gained even more popularity after the Asian crisis in the late 1990s. However, these crises drew attention to creating Early Warning System (EWS) models that could forecast currency crises (Berg, Borenztein and Patillo, 2004).

In light of the recent global financial crisis (the 2007 subprime collapse) it is clear that debt crises are costly and should be avoided. With particular focus on debt crises in South Africa, this paper will explore the methodology behind creating a functional EWS model. This paper will also create models that forecast debt crises in order to outline the approaches that can be taken to create such EWS models.

A debt crisis is not a new phenomenon. In fact, such crises go back as early as 4th century BC when 10 of the 13 Greek Municipalities defaulted on loan credit received from the Delos Temple (Winkler, 1933). Debt restructurings became practice following the defaults in France, Portugal and Spain in the 16th century (Reinhart, Rogoff and Savastano, 2003). It was in the 19th century that defaults and debt rescheduling agreements became even more common- this was mainly due to developments in the financial system, governments gaining independence and rising foreign loans (Sturzenegger and Zettelmeyer, 2006).

In the literature, the most common method of forecasting is to use the Logit model approach, although other methods such as Markov-switching have been suggested as being possibly more robust alternatives (Fedderke, 2011). Both of these approaches will be used. Additional approaches used in this study are: a graphical analysis as well as an Ordinary Least Squares (OLS) approach.

In order to motivate the importance of predicting and thus avoiding economic crises, I will briefly mention some of the effects of an economic crisis. Reinhart and Reinhart (2010), while assessing the affect of 18 crises on a country's economic proficiency, find:

- A decade after a financial crises or world-wide shock real GDP per capita growth rates remain significantly lower than their pre crisis levels. Generally, 1 percent lower.

- Unemployment rates increase post crisis by generally 5%. The authors also point out that out of 15 crises considered, 10 resulted in the unemployment rate not returning to previous levels.
- Following a crisis, the real housing prices decrease and remain low for up to ten years after the crisis.
- Deleveraging post crisis can take up to seven years.
- There are reductions in inflation post crisis.

Reinhart and Rogoff (2009) point out that, after a crisis, public debt may also rise. The authors suggest that in the post war period public debt may have increased by up to 86%.

Therefore, early warning systems are needed to attain "early signals that the pressure for a crisis may be building, allowing policy makers to undertake preventive measures in order to pre-empt the occurrence of crises." (Fedderke, 2011, pg 11)

The rest of this paper is organized as follows: Section 2 outlines the different types of financial crises; Section 3 looks at the underlying propagation mechanisms of a crisis. Section 4 reviews the empirical literature; Section 5 looks at the methodology behind creating Early Warning Systems and tabulates the data used in this study. Section 6 describes four different Early Warning System models; Section 7 conducts a graphical analysis and Section 8 concludes with recommendations for future research.

2. Types of Financial Crises

Early Warning System models have been created to attempt to forecast the onset of a crisis. In particular, there are six types of crises that one can attempt to forecast. Generally, the term financial crises refers to the three types of crises that are more common in the literature- currency crises, banking crises and debt crises; with currency crises being the most popular in the literature. A brief description of these crises is given below:

1. Currency Crisis- Such crises care broadly defined as currency devaluations or depreciations. This type of crisis is more visible than other types of crises. It also occurs more frequently and is thus the most studied type of crisis in the EWS literature. Currency depreciations lead to inflationary pressures and hence interest rate charges.

This leads to a lower growth and a higher rate of unemployment. Strong appreciations have a negative impact on exports and hence GDP.

2. Banking Crisis- A banking crisis refers to the situation when banks are unable to act as intermediaries. Banking crises can result in lower growth and a higher rate of unemployment due to a drop in investment, consumption and credit, brought about by the rising uncertainty in the market. A bank's inability to generate credit, and thus finance investment, will also have a negative effect on growth levels. Studies on banking crises include: Demirguc-Kunt and Detragiache (1998), Kaminsky and Reinhart (1998) and Lestano, Jacobs and Kuper (2003).
3. Debt Crisis- A debt crisis is generally defined as a situation where default on government debt occurs either under another countries jurisdiction (external debt crisis) or under the domestic countries jurisdiction (domestic debt crisis). Such crises result in lower growth, higher unemployment and spikes in the interest rate due to the defaulter's higher risk rating (Fedderke, 2011).

Other types of crises are: Asset Bubbles (these crises are associated with banking crises), Macroeconomic Crises (generally related to price stability or inflation) and Fiscal Crises (related to the sustainability of public finances).[1]

3. The Underlying Propagation Mechanisms of a Crisis

The theory-based literature on early warning systems is split into three groups based on the primary cause of the crisis.

The first generation models suggest that it is flaws in the domestic economy fundamentals drive instability. In this case focus is on the economic indicators that may suggest such economic disparities. The seminal contribution to first generation models was the speculative attack model by Krugman (1979). This model assumes that budget deficits are financed through monetization. Monetary authorities reduce their levels of foreign reserves in order to keep the exchange rate fixed. Such an approach is unsustainable as the central bank does not have an infinite supply or foreign reserves. Speculators know that this approach of fixing the exchange rate is unsustainable and this results in a speculative attack that takes place when the fixed exchange rate equals the

[1] The interested reader is referred to Fedderke (2011) for information on such crises.

shadow exchange rate.[2] Thus, reductions in reserves, increases in budget (or current account) deficits, growth in domestic credit or an overvalued exchange rate are early warning signals of a potential crisis or speculative attack.

The second generation view on financial crises is that a crisis can occur due to the role of expectations of economic agents. This allows for multiple equilibria to emerge. In the extreme case where agents have perfect information, expectations become self-fulfilling, making crisis prediction unfeasible.

The third generation approach to financial crises is concerned with contagion. Contagion refers to a situation where a crisis in one country increases the likelihood of a crisis occurring in another country. Although the studies of contagion do not use an identical definition of contagion, it can be generally defined as the spread of crises from one country to another. In the context of Early Warning Systems, it is necessary to distinguish between two types of contagion- pure contagion and shift contagion.

Shift contagion refers to a situation where a crisis is propagated through linkages between markets. Pure contagion, on the other hand, refers to crisis propagation between markets when there are no direct links between those markets. That is, under pure contagion, a crisis can spread between markets that are not economically linked, due to the perception and behavior of investors (Fedderke, 2011). Put differently, pure contagion results from the spill-over of idiosyncratic shocks rather than shocks to common fundamentals.

It is important for policy makers to know what the underlying propagation mechanism is as each distinction carries different policy implications.[3] For example, a shock that affects common fundamentals between markets will require temporary stabilization as well as intervention aimed at the domestic markets' structural features. Idiosyncratic shocks that have spilled over into other markets will also require temporary stabilization as well as talks with the authorities of the country hit by the shock, in order to improve regulation and reduce the chance that such a shock will reoccur (Fedderke and Marinkov, 2011).

Macroeconomic warning systems are concerned with domestic economic indicators and thus fit in with the first generation approach (Fedderke, 2011).

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[2] Note: The shadow exchange rate is that would occur under a floating exchange rate system.
[3] See Fedderke and Marinkov (2011) on how to identify the underlying cause of a crisis.

4. Empirical Literature Review

Four crises in the early to mid 1990's drew the attention of economists to the need to create an early warning system to signal the probable development of crises. They were the European Monetary System (ERS) crisis of 1992, the collapse of the Mexican Peso known as the Tequila crisis of 1994, the Asian flu of 1997 and the Russian virus of 1998 (Lestano, Jacobs and Kuper, 2003).

Much of the literature on Early Warning Systems is focused on currency crises; and the seminal works will be discussed here. Debt crises have received less attention in the literature and the relevant debt related papers will also be discussed in this section.

An early warning system is a system that has two components: "a precise definition of a crisis and a mechanism for generating predictions of crises" (Edison, 2000, pp3).

4.1 A precise definition of a crisis

4.1.1 A currency crisis definition

The literature contains a variety of definitions of crisis episodes. Eichengreen et al (1995) defines a currency crisis as either a successful speculative attack which results in significant movements in exchange rates or an unsuccessful speculative attack- an attack warded off by policy-makers.[4] Krugman (1979) defined currency crises as speculative attacks; the study assumed that the exchange rate remained fixed until a crisis ensued.[5] Kaminsky, Lizondo and Reinhart (1997) used the same crisis definition as Eichengreen et al (1995) but with one alteration- they did not include interest rate differentials.

4.1.2 A Debt Crisis Definition

The literature on debt crises commonly uses the concept of debt rescheduling as a definition for a debt crisis. Debt rescheduling refers to a situation where debtors negotiate a revised contract with their creditors. Such a revised contract may entail a reduction on the repayment and service of the debt as well as an extended period over which payment is made (Lestano, Jacobs and

[4] Unsuccessful speculative attacks are not easily observable, thus Eichengreen et al (1995) use sudden decreases in reserves or rises in the interest rate as indicative of such unsuccessful attacks.
[5] Connolly (1986) introduced crawling pegs to the model while Krugman and Rotemberg (1991) extended it to currency bands.

Kuper, 2003). Studies that have used this definition include Berg and Sachs (1988), Lanoie and Lemarbre (1996) and Marchesi (2003).

Another definition of a debt crisis comprises of three elements: 1. Debt rescheduling 2. The presence of the upper-tranche IMF agreement 3. Arrears that exceed some threshold level.[6] Studies that have used this definition of a debt crisis include Hajivassiliou (1989, 1994) and Ciarlone and Trebeschi (2006).

4.1.3 Equations used in the literature for defining a crisis

Earning warning mechanisms are necessary for forecasting the occurrence of a crisis. The most commonly used mechanisms are the Signals approach and the Logit approach. These two approaches require predetermined crisis periods. In this section I will briefly touch on the equations used by previous studies to determine currency crisis periods.

EWS models in the literature do not all use one agreed upon definition of a crisis. Generally, a crisis occurs when a variables moves above some threshold. The way in which an EWS defines a crisis will affect the number of crises it produces (Berg, Borenztein and Patillo, 2004).

There are a range of currency crisis pressure indicators that have been developed:

Eichengreen et al (1994) suggests the following specification for the pressure variable:

$$EMP1_{i,t} = \frac{1}{\sigma_e}\left(\frac{\Delta e_{i,t}}{e_{i,t}}\right) - \frac{1}{\sigma_{rm}}\left(\frac{\Delta RM_{i,t}}{RM_{i,t}} - \frac{\Delta RM_{US,t}}{RM_{US}}\right) + \frac{1}{\sigma_i}\left(r_{i,t} - r_{US,t}\right) \qquad (4.1.3.1)$$

The nominal exchange rate of the *i*th country in period t is $e_{i,t}$. The foreign reserves to M1 ratio is $RM_{i,t}$ while $r_{i,t}$ is the nominal interest rate. The reference country is the US. The standard deviations of the proportional changes act as weights and are given by σ. The reasoning behind this specification is that misaligned fundamentals may influence the maintainability of a currency's exchange rate. The pressure put on the currency in such a situation is what this specification attempts to pick up (Fedderke, 2011).

Kaminsky, Lizondo and Reinhart (1997) use the following equation to measure market pressure:

$$EMP2_{i,t} = \frac{1}{\sigma_e}\left(\frac{\Delta e_{i,t}}{e_{i,t}}\right) - \frac{\sigma_e}{\sigma_r}\left(\frac{\Delta RES_{i,t}}{RES_{i,t}}\right) + \frac{\sigma_e}{\sigma_r}\left(\Delta r_{i,t}\right) \qquad (4.1.3.2)$$

[6] Arrears refer to amounts that are unpaid after payment was due. The IMF agreement is outlined in IMF (2001).

RES stands for foreign reserves. This specification is simply a variant of Eichengreen et al's (1994) specification- the intuition behind it is the same as above.

Another variant of equation 4.1.3.1 is the definition used by Bussiere and Fratzscher (2002). Here, the weighted average of one-period proportional changes in the constituent variables is used to measure pressure on the sustainability of a given exchange rate. That is, they define the exchange rate pressure (EMP) as follows:

$$EMP3_t = \omega_{RER}\frac{\Delta RER_t}{RER_t} + \omega_r \frac{\Delta r_t}{r_t} + \omega_{RES}\frac{\Delta RES_t}{RES_t} \qquad (4.1.3.3)$$

Where RER is the real exchange rate, r is the interest rate, RES represents foreign reserves and the ω's are the relative weights such that more weight is given to more precise variables:

$$\omega_j = \frac{1}{var(j)}, j = \left(\frac{\Delta RER_t}{RER_t}, \frac{\Delta r_t}{r_t}, \frac{\Delta RES_t}{RES_t}\right) \forall t \qquad (4.1.3.4)$$

The intuition of this specification is the same as that of equation 4.1.3.1- briefly; this specification indicates the pressure on a given exchange rate of a currency due to misaligned factors.

Using the exchange rate pressure variable, EMP, one can now use the following equation to indicate periods of crisis:

$$CC_t = \begin{cases} 1 \ if \ EMP_t > \overline{EMP} + 2\sigma_t \\ 0 \ if \ EMP_t \leq \overline{EMP} + 2\sigma_t \end{cases} \qquad (4.1.3.5)$$

Where the EMP pierces the set boundary, a crisis is indicated. The idea to use two standard deviations to create the boundary is arbitrary. Eichengreen et al (1994) use 1.5 standard deviations above the mean to set the threshold. Kaminsky, Lizondo and Reinhart (1997) add 3 standard deviations to the mean to set their boundary. While Fedderke (2011) and Lestano, Jacobs and Kuper (2003) prefer setting the threshold at 2 standard deviations above the mean.

Frankel and Rose (1996) try a more direct specification, where the use of the underlying market pressure indicator (EMP) is avoided and the exchange rate is used directly to indicate a crisis:

$$CC_{i,t} = \begin{cases} 1 \ if \ \%\Delta e_{i,t} > 25\% \ and \ \%\Delta e_{i,t} > 10\% + \%\Delta e_{i,t-1} \\ 0 \ otherwise \end{cases} \qquad (4.1.3.6)$$

This specification is simpler and more explicit than that of equations 4.1.3.1 to 4.1.3.3.

4.2 A mechanism for generating predictions of crises

Once the crisis periods are defined, a EWS model is needed to forecast the onset of such crises. The approaches used in the literature to forecast crisis episodes are discussed here.

4.2.1 Estimating Structural/ Theory Based Models

4.2.1.1 Estimating First Generation Models

The studies by Blanco and Garber (1986) and Edin and Vredin (1993) are early attempts at creating models to explain and predict crises. Both papers focused on currency crises and set out to empirically estimate structural first generation models (Abiad, 1999). Using quarterly data for Mexico over the period 1973- 1981, Blanco and Garber (1986) looked at recurrent devaluations in the context of the speculative attack model. Using monthly data over the period 1979-89 for four Nordic countries, Edin and Vredin (1993) studied devaluations with regard to bands and target zones. The in-sample performance of both models was satisfactory. In fact, the Mexican devaluation of 1982 was forecasted by Blanco and Garber (1986). However, these models were limited. That is, they were only able to look at pressures brought about by monetary imbalances[7] - no other sources of pressure were considered. However, since other indicators may change their behavior in the periods surrounding crises, the literature has looked for less restrictive approaches whereby a multitude of indicators can be considered. Thus, the approaches for developing early warning systems moved away from empirical estimates of theory based models to approaches where one has complete freedom in choosing the indicator variables (Abiad, 1999).

4.2.1.2 Cross Country Regression for Looking at Contagion

Sachs, Tornell and Velasco (1996) looked at how the Mexican crisis in 1994 affected the other emerging markets the following year. The study used cross sectional data for 20 countries in 1995. Due to the cross sectional nature of this approach, it does not provide insight regarding the timing of a crisis but it does indicate which countries are more likely to experience more severe crises when global changes occur. That is, the study aims to determine which macroeconomic indicators explain the vulnerability of different countries to contagion effects. Originally this

[7] For example: domestic credit growth in Blanco and Garber’s study. The indictors used in Edin and Vredin’s study were: money, output, the foreign interest rate, foreign price level, the real exchange rate, foreign reserves/ imports and the trade balance.

approach was aimed at explaining the Mexican crisis but has since been applied to the Asian crisis.[8]

4.2.2Event Study Analysis

Event study analyses have been used in the literature to examine the behavior of variables before a crisis occurs and after the crisis has taken place. Thus, both the "seeds" and the "aftermath" of a crisis can be studied (Frankel and Rose, 1996, pp 359). Event study analyses have been used in the currency crisis literature by Eichengreen et al (1995) and Frankel and Rose (1996). In the debt crisis literature, it has been used by Ciarlone and Trebeschi (2006). Here, I will briefly outline the Event Study methodology found in Frankel and Rose (1996).

Frankel and Rose (1996) refer to a currency crash as a situation where a substantial depreciation in the nominal exchange rate (at least 25% against the US dollar) is also at least 10% greater than any depreciation in the previous year. Annual data from 1971 to 1992 for 105 developing countries was used. The authors investigated numerous different indicators that may affect how vulnerable a country is to a crisis. When defining crisis periods, Frankel and Rose made use of an exclusion window; they ignored crises that took place within three years of each other so that no double counting took place. Observations that do not lie in the exclusion window and are non crisis observations are termed tranquil observations and are used as a control for comparing the behavior of a variable around a crisis period. Frankel and Rose (1996) illustrate the behavior of 16 possible indicator variables, each on a separate set of axes. This shows the movements of the variables three years before and after a crisis. For comparative purposes, a horizontal line is included in each graph, representing the averages for the tranquil periods. Although these univariate graphs provide some insight, one cannot infer from them what the marginal input of each variable is. Therefore, Frankel and Rose (1996) introduce the probit approach.

4.2.3The Logit/ Probit Approach

In their 1996 paper, Frankel and Rose set out to define "currency crashes" and then forecast them using both an event study analysis as well as the probit approach.[9] They use the probit approach to try forecasting the probability of a crisis occurring, one year ahead. Most of the coefficients in their contemporaneous regression are found to not be statistically significant. In their regression

[8] See Berg and Patillo (1999)
[9] The methodology behind the probit approach can be found in section 5.5 of this paper.

where all the indicator variables were lagged by one year, the authors achieved results that echoed Krugman's (1979) model of speculative attacks.

The literature is predominantly focused on currency crises. However, following the crises in Turkey in 2002 and Brazil in 2001, there has been growing interest in EWSs for debt crises (Ciarlone and Trebeschi, 2006). Below is a brief discussion on the studies that have used the logit/probit approach to forecast debt crises.[10]

Lanoie and Lamarbre (1996) and Marchesi (2003) used probit models to create early warning systems for debt crises. Lanoie and Lamarbre (1996) used annual data from 1983 to 1996 for 87 countries and found that the ratio of the current account to GDP was a significant crisis indicator variable. Marchesi (2003) used annual data from 1989 to 1990 for 93 countries.

Lestano, Jacobs and Kuper (2003) create a EWS for 6 Asian countries using data from 1970 to 2001. Logit models are created for a banking crisis, a currency crisis and a debt crisis. The authors use debt rescheduling as their definition of a debt crisis. They used factor analysis to reduce the number of potential indicators; after which, the indicators are used as the right hand side variables in a logit model. Broadly, they conclude that financial crisis indicators do provide useful information regarding the onset of a crisis. The debt crises models used in their study performed well for signaling crises in Indonesia. The out-of-sample models in their study performed poorly.

Ciarlone and Trebeschi (2006) used a multinomial approach to develop a EWS for debt crises. While Bussiere and Fratzcher (2002) applied a multinomial logit to currency crises, Cialone and Trebeschi (2006) were the first to apply this approach to debt crises. Data was used from 1980 to 2002 for 28 emerging market countries that had access to international capital markets. The authors also conducted an event study analysis to illustrate the behavior of indicator variables around a crisis period. Their model performed well both in- and out-of-sample.

4.2.4 Signals Approach

Kaminsky and Reinhart (1996) and Kaminsky, Lizondo and Reinhart (1997) developed the signals approach. This approach looks at the behavior of indicator variables before a crisis took

[10] To see how the logit approach can be applied to any type of crisis, see Fedderke (2011). Demirguc-Kunt and Detragiache (1996) apply the logit/ probit approach to banking crises.

place. In this approach the indicator variables are made into binary variables. The dependent variable is also binary.

The methodology developed by these two studies is present below:

The signals approach connects the binary crisis indicator variable (CC_t) to a number of signal variables.[11] Signal variables are chosen either on theoretical grounds or because they have experienced significant changes in their behavior before a crisis. Signal variables are denoted S_t such that $S_t=\{0,1\}$. S_t takes on a value of 1 when a signal is generated. Such a signal is generated when the indicator (X_t) exceeds a threshold (X^*).[12] That is,

$$S_t = \begin{cases} 1 \ if \ |X_t| \geq |X^*| \\ 0 \ if \ |X_t| < |X^*| \end{cases} \tag{4.2.4.1}$$

The classification of signals is intuitive; a good signal is followed by a crisis within some predetermined period of time, a bad signal is not. The more indicators sending out signals, the more concerned one should be about a crisis ensuing. The threshold used in equation 4.2.4.1 is not arbitrary. The threshold is chosen to maximize the signal to noise ratio i.e. the ratio of good signals to bad signals. Such a ratio is also useful for the ranking and dropping of indicators. There is a tradeoff between false signals and missed crises and the threshold is chosen to balance this trade-off. Recall, it is in the calculation of CC_t that the threshold is chosen is arbitrary.

	Crisis	No Crisis
Signal	A	B – Type II error: False positive signal
No signal	C –Type I error: False negative signal	D

Table 4.2.4.1[13]: Evaluating the accuracy of the Signals Approach

Using table 1, the predictive performance of indicator variables can be assessed. Examples of possible assessment criteria are mentioned below:

[11] See section 4.1.3 for the equations used, in the literature, to create the CC variable.
[12] To incorporate both positive and negative shocks, the absolute value of the signal variables is used.
[13] Source: Fedderke (2011)

1. The simple accuracy criterion: This criterion seeks to maximize the ratio of correct calls to total calls, $\frac{A+D}{A+B+C+D}$, or minimize the ratio of false calls to total calls, $\frac{B+C}{A+B+C+D}$.
2. Another criterion involves minimizing the occurrence of type II errors. Policy makers, with financial systems that are to some degree stable, may want to minimize such false positives as intervention may be both costly and inefficient. In this case, it is the ratio $\frac{B}{B+D}$ that one wants to minimize or $\frac{D}{B+D}$ that one wants to maximize.
3. It is also feasible that one would want to minimize the occurrence of false negatives (type II errors). Policy makers who are interested in avoiding crises regardless of the cost and inefficiency of intervention would be particularly interested in this objective. Here, one seeks to minimize $\frac{C}{A+C}$ or maximize $\frac{A}{A+C}$.
4. There is a trade off between type I and type II errors and one may be interested in balancing this trade off. For example, Kaminsky, Lizondo and Reinhart (1997) set the threshold at a level that minimized the noise to signal ratio, $\frac{B}{B+D} \Big/ \frac{A}{A+C}$. This is equivalent to writing $\frac{Type\ II\ error}{1-Type\ I\ error}$. If this ratio is less than one the indicator is classified as a useful predictor.

The time horizon of the signals has to be chosen; signals that forecast a crisis over a short time horizon may be accurate but may not provide enough time for intervention. A longer time horizon may lose accuracy. Kaminsky, Lizondo and Reinhart (1997) choose a time horizon of 24 months.

The advantages of the signaling approach stem from the fact that indicators can be individually examined allowing one to identify which the more important ones are. Also, the number of indicators exhibiting erratic behavior gives an indication of the scope of the problems.

There are two disadvantages to the signaling approach: it cannot be statistically tested or easily compared to the other approaches and marginal contributions are not assessed, meaning that if variables hold some common information that causes them to move in the same direction and emit signals together, they will all be included as separate variables with the same weights (Abiad, 1999).

The signals approach does not make use of a model but rather monitors the signals produced and the amount of indicators producing good signals (Abiad, 1999). Kaminsky, Lizondo and Reinhart (1997) find that the signals approach works well; on average, the range of indicators correctly forecast 70% of the crisis periods.

The literature on the signals approach has expanded since Kaminsky, Lizondo and Reinhart's work; especially since their approach ignores the fact that some indicators may be more accurate than others. Kaminsky (1998a) uses a weighted average of the signals to create a composite indicator where the accuracy of each indicator is reflected in the weights. Berg and Patillo (1999) suggest using the indicators as explanatory variables in a logit/probit model. Kaminsky (1998a and 1998b) and Goldstein (1998) tested the forecasting performance of the signaling approach and found that it would have been a decent EWS mechanism for the Asian crisis.

Edison (2000) further developed the signals approach to create a EWS for currency crises. Edison modifies the work of Kaminsky, Lizondo and Reinhart by adding 8 countries to their original 20 as well as using 7 additional indicators. Edison (2000) found that the additional variables were important additions to the EWS in Kaminsky, Lizondo and Reinhart's (1997) paper, while the addition of the countries was not. The EWS that Edison (2000) created indicated vulnerability in the Asian countries a few months before the start of the crisis. Overall, the results are mixed- some indicator variables gave off early warning signals but many false alarms were generated.

4.2.5 Comparing the Different Approaches

Berg and Patillo (1999) used EWS models that were formulated before 1997 to investigate whether they would have been able to predict the Asian crisis had they been in use prior to the crisis. They found that the signals approach would have been more insightful than a random guess but does not predict the timing of a crisis very well. It was, however, a satisfactory approach for ranking countries according to the magnitude of a crisis. The authors find that the probit model of Frankel and Rose (1996) does not provide a satisfactory prediction of the Asian crisis. Berg and Patillo (1999) apply the cross sectional approach pioneered by Sachs, Tornell and Velasco (1996) to the Asian crisis and find the forecasting performance poor.

Berg, Borenztein and Patillo (2004) compare the predictions of Kaminsky, Lizondo and Reinhart's signals approach to model independent indicators, for example bond spreads. Such non-model based indicators have been used by policy makers since the Mexican Peso Crisis which began in 1994. They found that the signals approach outperforms the independent indicators. The authors then look at four different models to see which are useful predictors of impending crises. The models are KLR (Kaminsky, Lizondo and Reinhart's 1997 model), DCSD (the Developing Country Studies Division model), CSFB (the Credit Suisse First Boston model) and GS (the Goldman Sachs model). The KLR model performs well both in- and out-of-sample. The DCSD model is informative but performs better in-sample that out-of-sample. The other two models perform well in-sample but poorly out-of-sample.

4.2.6 An Alternative Approach: The Markov-Switching Approach

Abiad (1999) used a Markov-switching model with time varying probabilities on data from Indonesia, Malaysia, the Philippines and Thailand during 1974-1998. The model's predictive performance was analyzed both in- and out-of–sample with the out-of-sample period starting in mid 1997. The model's full-sample performance was satisfactory; signals were sent out for Thailand and Malaysia. The model was less informative for Indonesia and the Philippines. Out-of-sample, the model performs well in the case of Thailand and poorly in the case of Malaysia. No out-of-sample testing was done for Indonesia and the Philippines due to the dissatisfactory full-sample results for these countries. The results fit well with the work of Radelet and Sachs (1998) that suggests that the crisis in Thailand began due to first generations effects while the underlying cause of the crisis in Indonesian and the Philippines is related to contagion.

Fedderke (2011) outlines the steps behind creating early warning systems for the 15 SADC countries. In this paper, the steps to creating an early warning system are generalized so that they can be applied to any context. That is, one can create an EWS for any type of crisis.

5. The OLS approach, the Logit/probit approach, the Markov-switching approach and the data.

One approach that is very popular in the literature on Early Warning Systems is the logit/probit approach. The Markov-switching approach exists as an alternative to this approach. The mechanics behind these two approaches will be discussed in this section. This section will also introduce a third approach whereby EWS models are created using ordinary least squares (OLS).

5.1 Defining a Crisis Period

This paper will use the following general set up, as suggested by Fedderke (2011), to measure market pressure. This specification is chosen as it is simple and does not require any ad hoc special weights to any variables.

$$DPV_t = \sum_{k=1}^{n} \omega_{X_k} \frac{\Delta X_{k,t}}{X_{k,t-1}} \quad (5.1.1)$$[14]

$$\omega_{Xk} \frac{1}{var(X_k)}, k = (1, \dots, n) \forall t \quad (5.1.2)$$

For the debt crisis case, the market pressure variable used will be referred to as DPV_t. X_k is the kth constituent variable of the models pressure indicator and $var(X_k)$ is its variance. w_{xk} is the weighting assigned to the kth explanatory variable. In this case the explanatory variables are domestic private sector debt as a proportion of GDP (DPrYt), foreign private sector debt as a proportion of GDP (FPrYt), domestic public sector debt as a proportion of GDP (DPuYt), foreign public sector debt as a proportion of GDP (FPuYt) , foreign reserves (RESt) and the real exchange rate (RERt) (Fedderke, 2011). Thus the market pressure equation would be:

$$DPV_t = \omega_{DPrY} \frac{\Delta DPrY_t}{DPrY_t} + \omega_{DPuY} \frac{\Delta DPuY_t}{DPuY_t} + \omega_{FPrY} \frac{\Delta FPrY_t}{FPrY_t} + \omega_{FPuY} \frac{\Delta FPuY_t}{FPuY_t} + \omega_{RES} \frac{\Delta RES_t}{RES_t} + \omega_{REER} \frac{\Delta REERt}{REER_t} \quad (5.1.3)$$

where

$$\omega_J = \frac{1}{var(j)}, j = \left(\frac{\Delta DPrY_t}{DPrY_t}, \frac{\Delta DPuY_t}{DPuY_t}, \frac{\Delta FPrY_t}{FPrY_t}, \frac{\Delta FPuY_t}{FPuY_t}, \frac{\Delta RES_t}{RES_t}, \frac{\Delta REER_t}{REER_t} \right) \quad (5.1.4)$$

Using the market pressure variable for a debt crisis (DPV), debt crisis periods can now be determined. This is done by setting a boundary and looking at where the DPV pierces this boundary. This boundary is arbitrarily set. Some studies have set the boundary as the mean plus 1.5 standard deviations (For example, Eichengreen et al, 1995), Kaminsky, Lizondo and Reinhart

[14] All equations found in this subsection are from Fedderke (2011)

(1997) set the boundary as the mean plus 3 standard deviations. Although all the studies agree that the boundary is arbitrarily set, it is commonly set as the mean plus two standard deviations in the literature. In this paper, I will set the boundary as the mean of the DPV variable plus 1.75 of its standard deviations. Thus, the upper boundary is equal to 112.12 while the lower boundary is equal to -101.41. Adding 1.75 standard deviations to the mean allows me to pick up two additional crises that would not have been indicated by using a more conventional boundary. That is, crisis periods, CC_t, are defined as follows[15]:

$$CC_t = \begin{cases} 1 \text{ if } DPV_t > \overline{DPV} + 1.75sd(DPV) \\ 0 \text{ if } DPV_t \leq \overline{DPV} + 1.75sd(DPV) \end{cases} \tag{5.1.5}$$

The debt pressure variable piercing the upper boundary indicates that debt levels as a share of GDP have risen substantially. Such high levels of debt may not be sustainable and this is reflected through increases in the debt pressure variable. The DPV piercing the lower boundary indicates that debt levels as a share of GDP have fallen. This has a contractionary effect on the economy. The 2007 subprime collapse is an example of the case where debt levels increased substantially, but not sustainably; an upper boundary piercing by the DPV. The withdrawal of loan capital by foreign banks led to South Africa's major debt crisis in the late 1980s; which was followed by a major recession in the early 1990s. This situation is an example of how decreases in the DPV can have contractionary effects. Given these two examples, it is clear that one should be concerned about piercing both the upper boundary as well as the lower boundary.

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[15] Exclusion windows are used by researchers who are specifically interested in the *onset* of a crisis. That is, an exclusion window refers to a situation where the researcher ignores crises that take place within j-periods of each other (Abaid, 1999). A three year exclusion window was used by Frankel and Rose (1996) while Eichengreen et al (1995) used a one quarter exclusion window. Mathematically, an exclusion window is a modification to the definition of the crisis variable CC_t. For example, for the debt crisis variable mentioned above in equation 5.1.5:

$$CC_t = \begin{cases} 1 \text{ if } DPV_t > \overline{DPV} + 1.75sd(DPV) \text{ and } CC_{t-j} = 0 \text{ for } j = 1,2,\ldots,J \\ \qquad\qquad 0 \text{ otherwise} \end{cases}$$

Abaid (1999) points out a problem with an exclusion window. Independence across observations is assumed in a logit/probit model but the addition of an exclusion window implies that $Pr(CC_{t+j} = 1) = 0$ when $CC_t = 1 \text{ for } j = 1,2,..J$

Exclusion windows will not be used in this study for this reason.

The equations used to define crisis periods may not identify all crisis cases. The debt pressure variable may rise without piercing the boundary and judgment may be required to decide whether or not it constitutes a crisis. For example, during the currency crisis in Sri Lanka in 2000, no month was particularly distressing. Thus, EWS models analyzing the period registered it as a close call but not a crisis (See Berg, Borenztein and Patillo, 2004).

5.2 The Data and Calculation of Debt Pressure Variable, DPV, and the binary CC variable

Data from the South African Reserve Bank, SARB[16], was used for this paper. The debt pressure variable (DPV) was calculated at a quarterly frequency from 1985-Q2 until 2010 –Q4. This was done because the constituent variables used to calculate the DPV were available in monthly frequency, except for one variable which was available in yearly frequency. Averaging monthly variables to quarterly data and interpolating yearly data to quarterly data results in a smaller error than that if annual data was interpolated to monthly data. Also, the majority of the indicator variables used to forecast debt crises (see table 5.3.1) are only available as quarterly data. The variables used to calculate the debt pressure variable, DPV are as follows:

Variable	Description	SARB code	Transformation
Public Sector Domestic Debt	Total loan debt of national government: Total domestic debt, measured in R millions.	4105M	This variable was averaged into quarterly data.
Public Sector Foreign Debt	Total loan debt of national government: Total foreign debt	4108M	This variable was averaged into quarterly data
Private Sector Domestic Debt	All monetary institutions : Credit extended to	1369M	Averaged into quarterly data

[16] South African Reserve Bank data can be found on their website: www.resbank.co.za

	the domestic private sector: Total loans and advances		
Private Sector Foreign Debt	Foreign debt of S.A.: Private sector	5529J	This variable was interpolated into quarterly data
GDP	Gross domestic product at market prices (GDP) current prices	6006K	
RER	The Real Effective Exchange Rate	5378M	This variable was averaged into quarterly data
RES	Foreign Exchange Reserves, measured in R millions	5284M	This variable was averaged into quarterly data

Note: M indicates monthly data while K and J indicate quarterly and annual data respectively.

Table 5.2.1: Variables used, in equation 4.10, for defining debt crisis periods.[17]

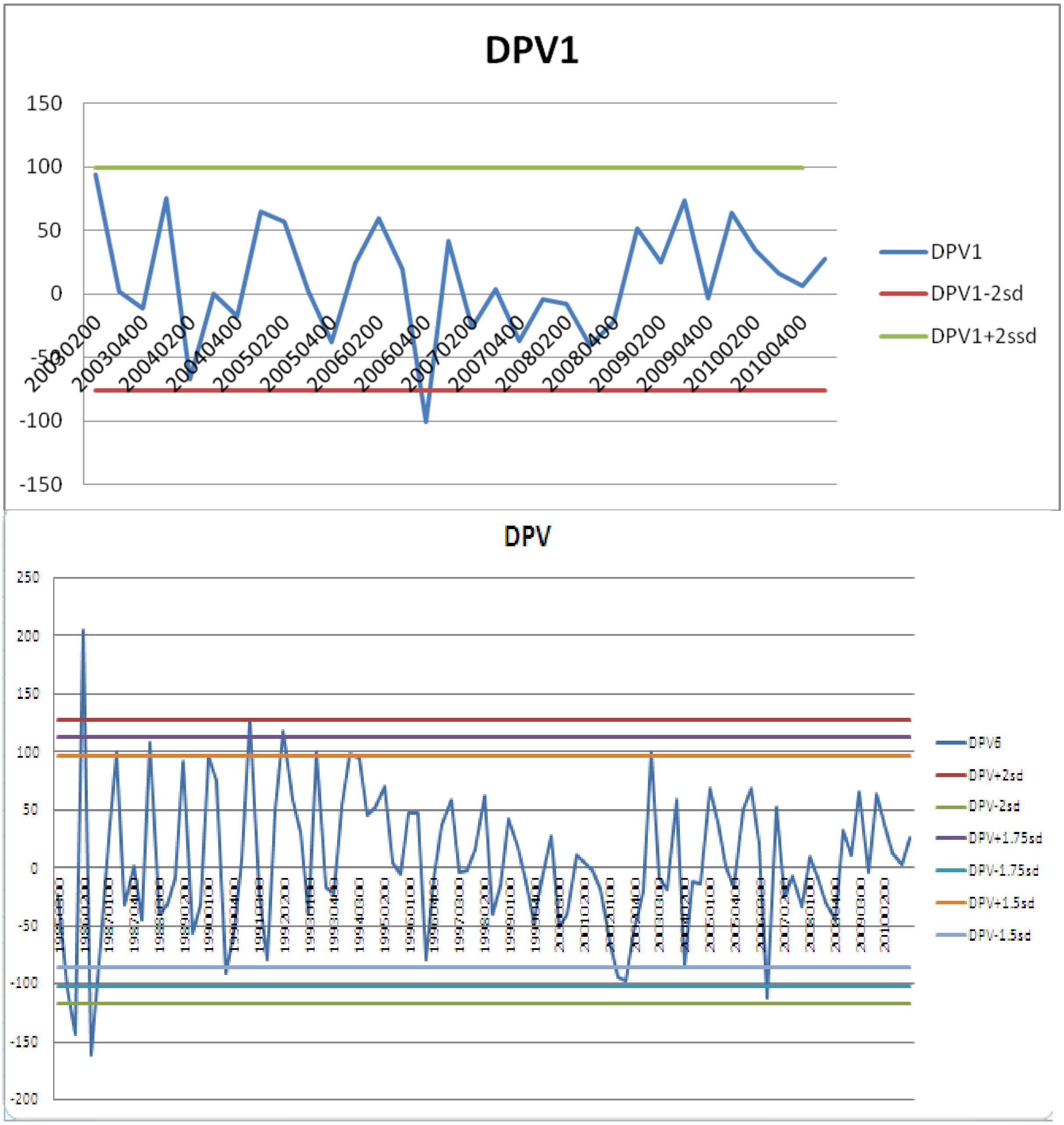
Looking at table 5.2.1 it is clear that some information may be lost during the averaging procedure.[18] Averaging can "smooth out" data and thus eliminate potential crises. At the same

[18] The averaging procedure involves calculating the average over three months of a variable and using that average as a quarterly observation in the quarterly data set that one is aiming to create.

time, “a month does not a crisis make” (Abiad, 1999, pp 18). That is, if a crisis is only indicated for a single month, it may not necessarily reflect a substantial structural problem. The aim of this paper is to look at the approaches to creating an early warning system for a debt crisis- a substantial structural problem rather than a temporary misalignment. Therefore, although averaging monthly data into quarterly data is not ideal- it is less of an issue for the context of this paper.

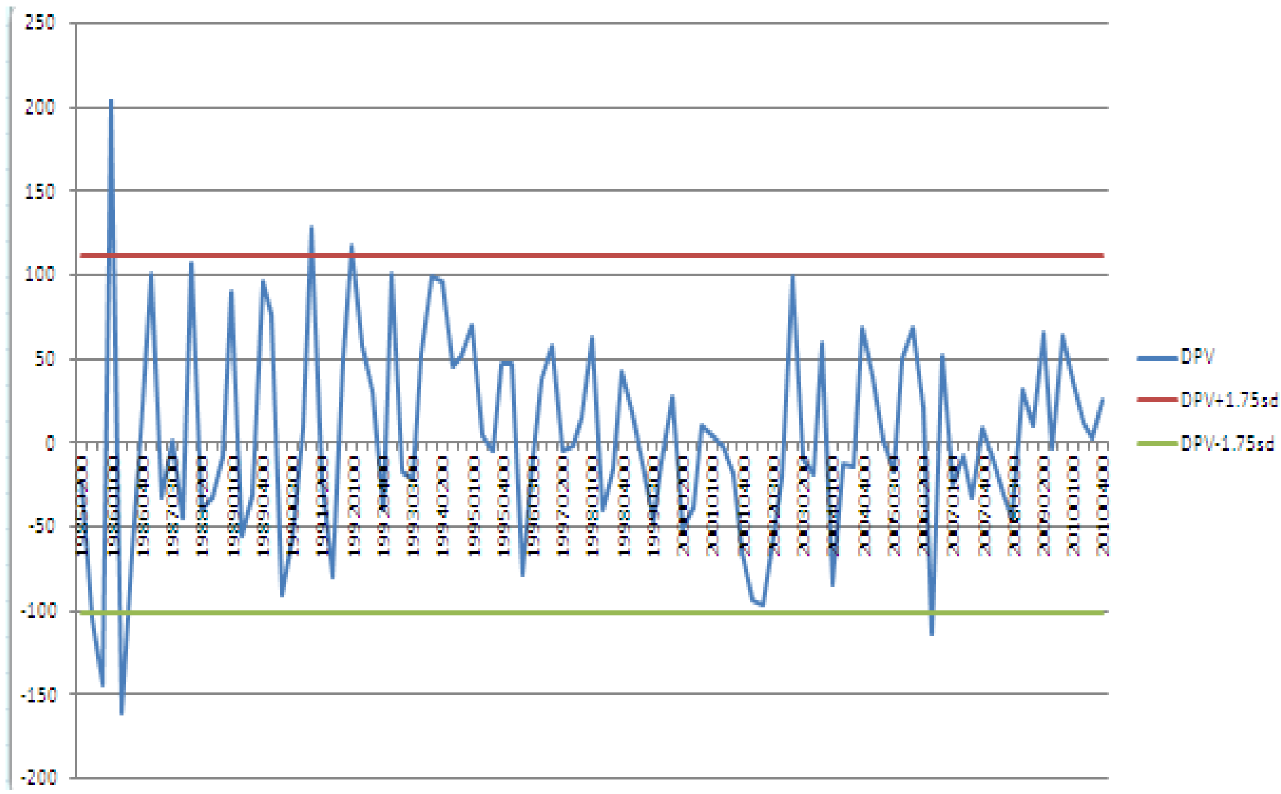
Interpolation of the private sector foreign debt variable also may result in a loss of accuracy.[19] Quarterly data on private sector foreign debt was only available from 2002 while the annual data was available for the entire period of this study. A description of the annual data can be found in Table 5.2.1. The quarterly data used as a proxy for this variable can be found by summing the “Banking Sector” and “Other Sectors” columns of the quarterly external debt data from SARB and then multiplying each observation by the exchange rate for that period in order to convert the Dollar denominated data into Rands. The annual data for private sector foreign debt was interpolated into quarterly data and used to calculate the market pressure variable. Substituting the interpolated data with the quarterly data and looking at the debt pressure variable from 2002 onwards yielded a similar DPV graph. Thus, interpolation has not distorted the private sector foreign debt variable and the annual data will be used rather than the quarterly data as it is available for a longer time period. However, in the case where the quarterly private sector external data was used, the debt pressure variable (DPV1) pierced the lower boundary in 2006-Q3 where the boundary is calculated as the mean plus 2 standard deviations (see graph 5.2.1). The debt pressure variable calculated from annual interpolated data does not indicate a crisis in 2006-Q3. By calculating the boundary of the debt pressure variable (DPV) as the mean plus 1.75 standard deviations, the 2006-Q3 crisis is picked up. In this study, I will calculate the debt pressure variable using the annual data for private sector foreign debt since it is available for a longer time period and thus allows me to try to forecast the biggest debt crisis in South Africa- the foreign debt crisis of 1985. I will however, set my boundary at 1.75 standard deviations added to the mean in order to pick up the 2006-Q3 crisis.

[19] Linear interpolation is used in this paper to transform annual data into quarterly data: the difference between each year is calculated and divided by four. Quarterly observations are created by adding a fourth of this difference to the starting year, and then adding a fourth of the annual difference to that, and so on.

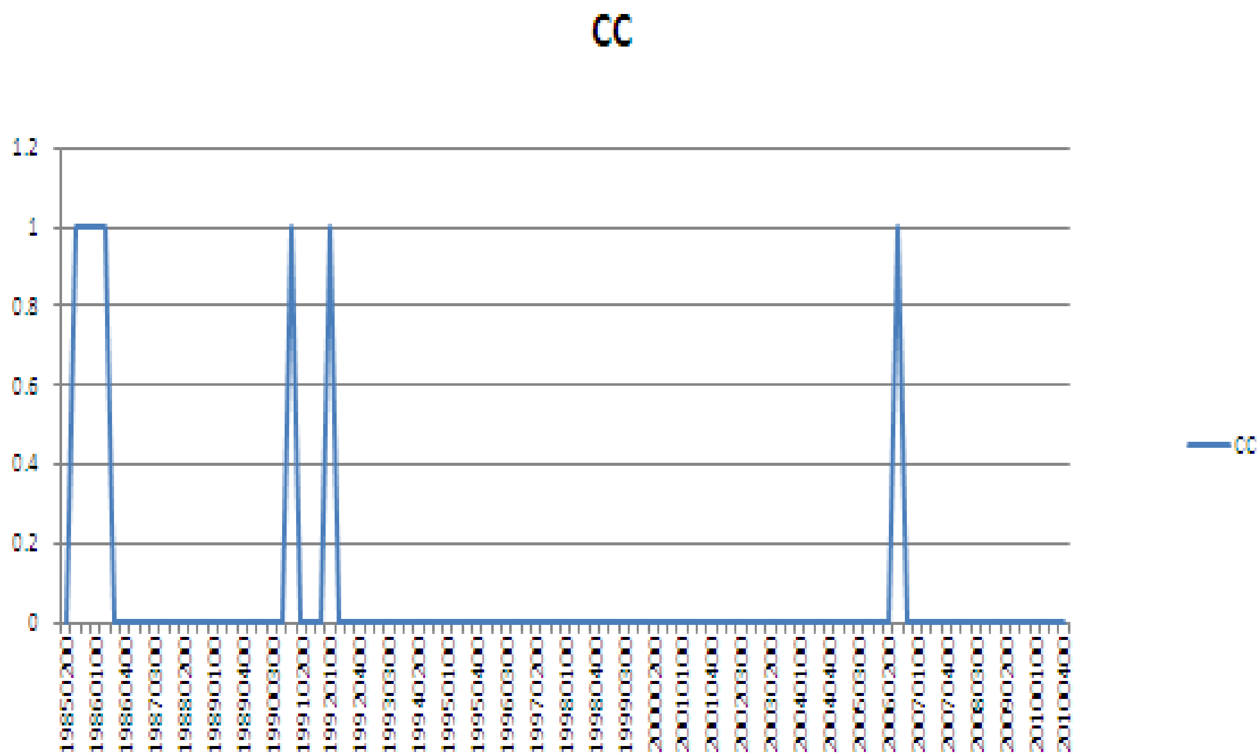


Graph 5.2.1: DPV1 is the debt pressure variable calculated from the quarterly external debt data from SARB. DPV is the debt pressure variable where the annual data on private sector foreign debt (see table 5.2.1) is used.

The DPV variable as well as the boundary levels that will be used in this study are graphed below:



Graph 5.2.2: The debt pressure variable (DPV) calculated as per equation 5.1.3 and 5.1.4. Included in the graphs are the boundaries, calculated as the mean plus 1.75 standard deviations of the DPV variable.



Graph 5.2.3: The CC variable, calculated as per equation 5.1.5, indicates the crisis periods. Spikes in the CC variable correspond to the points where the DPV variable pieces the boundary, indicating a crisis period.

Berg, Borenztein and Patillo (2004) point out that crisis dates are pin pointed in EWS models even though the occurrence of such crises are not perfectly identified. Thus, "the specification of EWS models involves a number of decisions that, while guided in some way by economic theory, are largely empirical and judgmental in nature" (Berg, Borenztein and Patillo, 2004, pp4). The crisis dates arrived at from equation 5.1.5 are discussed in the table below:

Crisis Periods	Corresponding Economic Events in South Africa
1985-Q3 Until 1986-Q2	In the late 1970s, loans were easily attainable and thus extensive borrow by the private and public sector took place. Foreign investments decreased in the early 1980s. The South African government assisted with loan capital whenever credit extensions were refused by foreign banks. The government financed such loans through gold swaps or by using funds borrowed from the IMF. Sanctions on the South African economy were placed in the 1980s and early 1990s. Such sanctions included the ban on IMF loans in 1983, a 1985 prohibition of many foreign bank loans, the United States 1986 Comprehensive Apartheid Act and the 1986 EEC (European Economic Community) prohibition on investments and trade. In 1985 a major foreign debt crisis took place. This was mainly because short term loans were immediately withdrawn in 1985 by a group of foreign banks. A debt rescheduling contract was drawn up; it stipulated that a debt freeze would continue until June 1987 at least (Byrnes, 1996).
1991-Q1 and 1992-Q2	Although in 1991 the United States and the EEC had withdrawn their sanctions, foreign investors viewed SA as unstable, with high labor costs. High levels of consumer indebtedness as well as fears of violence and job losses were major restrictions on private consumption. There was a decrease in GDP in 1991 and 1992. The Major Debt Crisis in the late 1980s had forced South Africa to have current account surpluses for repayment purposes. In 1991 there was a drastic increase in the surplus. A major recession occurred from March 1989 to May 1993 (Byrnes, 1996). In 1991-Q1 the real exchange rate increased, there was also an increase in the level of foreign reserves. Although private sector foreign debt as a share of GDP had be declining since 1985, it did show a slight increase in 1991-Q1. Both private and public sector domestic debt as a share of

	GDP showed increases for the beginning of 1991. In 1992-Q1 the level of foreign reserves was higher. Debt as a share of GDP (both external and domestic for both the public and private sector) increased in 1992-Q1.
2006-Q3	Turbulence hit the financial markets in May 2006. In June 2006 interest rates increased by 200 basis points. By mid 2006 the international price of crude oil was high, the rand exchange rate had weakened and food prices had risen. In fact, there was a currency crisis in June 2006 (see Knedlik and Scheufele (2007)). This put pressure on inflation (Fourie, 2006). Public sector debt decreased in relation to GDP. Private sector debt as a share of GDP, which had been rising since the end of 2004, declined in 2006-Q3 before rising again.

Table 5.2.2: Description of the crisis periods

5.3 Data used for the Indicator Variables

After defining the crisis periods, the next part of creating an EWS involves finding a model that forecasts these crisis periods. These models are discussed in section 6. The indicator variables used in these models are tabulated below (in table 5.3.1). Many of these indicator variables are chosen from a list of variables suggested by Fedderke (2011) as being potentially important for explaining a crisis. This list is comprised of variables that studies on debt crises, such as Lestano, Jacobs and Kuper (2003), have used as indicator variables. For example, Leoni and Lamarbre (1996) and Marchesi (2003) found that the probability of a debt crisis occurring increases with a low rate of growth of per capita GDP and high levels of capital inflows. Lestano, Jacobs and Kuper (2003) found the growth of money (M1 and M2) and the growth of per capita GDP to be significant indicators. The indicators that were found to be statistically significant in Ciarlone and Trebeschi (2006) include macroeconomic indicators, such as the growth rate of real GDP, as well as measures of both external debt and how it is financed. Fedderke's (2011) list can be found in the appendix to this paper (see table A1). Table 5.3.2 briefly outlines why the chosen indicator variables may be important in explaining a debt crisis. The expected sign of each variable are also included in table 5.3.2.

Unless otherwise indicated, the indicator variables used in this study can be found on South African Reserve Bank's (SARB) website[20]. They are listed in the table below.

Variable	Description and Frequency	Transformation	Name used in equations	Source and code
Current account/GDP	Ratio of current account balance to gross domestic product. (Percentage). Quarterly		CA/GDP	SARB KBP5380K
Investment/ GDP	Gross fixed capital formation (Investment). Quarterly	Investment was divided by GDP and then first differenced in order to make it stationary	INV/GDP	SARB Investment: KBP6009K GDP: 6006K
GDP/capita	GDP divided by Population size. Quarterly	GDP was divided by the population size and then first differenced in order to make it stationary	GDP/cap	GDP: SARB KBP6006 Population Size: IFS 19999Z ZF
Growth in reserves	Foreign Exchange Reserves.	The percentage change in Foreign	% Chg RES	SARB

[20] See www.resbank.co.za

	Monthly- averaged to quarterly	Reserves was used		KBP5284M
Savings/GDP	Ratio of gross savings to GDP. Quarterly	This variable was first differenced in order to make it stationary	Chg Sav/GDP	SARB KBP6286
M2	Monetary aggregates, money supply. Monthly	This variable was first differenced in order to make it stationary	Chg M2	SARB KBP1373
Terms of Trade	Foreign Trade: Terms of Trade: Excluding gold. Quarterly	This variable was first differenced in order to make it stationary	Chg TOT	SARB KBP5036L
Real GDP	GDP at constant 2005 prices Quarterly	This variable was first differenced in order to make it stationary	Chg GDPcon	SARB KBP 6006C
Gold Price	The historic price of gold in Rands. Average for the quarter.	The dollar value was multiplied by the Rand/Dollar exchange rate (see below). The natural logarithm of this variable was taken, then the first	Chg Ln Gold	Bundesbank[21] WP183HC

[21] See http://www.bundesbank.de

		difference was calculated in order to make it stationary.		
Oil Price	The price of Crude oil in Rands.(per barrel). Average for the quarter.	The dollar value was multiplied by the Rand/Dollar exchange rate (see below). The natural logarithm of this variable was taken, then the first difference was calculated in order to make it stationary.	Chg Ln Oil	Dow Jones and Company[22] OILPRICE
The Spread	The South African interest rate (Rsa): Yield on loan stock traded on the stock exchange: Government bonds - 0 to 3 years (percentage) The U.S. interest rate (Rus): Market yield on U.S. Treasury	South African interest rate (Rsa) minus the interest rate in the U.S.(Rus) Rsa-Rus This variable was first differenced in order to make it stationary	Chg Rsa-Rus	Rsa: SARB KPB2000 Rus: The Federal Reserve Bank[23] H15/H15/RIFLGF CM03_N.M

[22] See www.dowjones.com
[23] See www.federalreserve.gov

	securities at 3-month constant maturity, quoted on investment basis (percentage). Monthly-averaged into quarterly.			
The Rand Dollar Exchange rate	The Rand Dollar exchange rate was used to convert the gold and oil prices into Rands. Averaged into quarterly data.			Federal Reserve Bank of St Louis FRED.EXSPUS

Table5.3.1 Indicator Variables used for the logit approach and OLS approach.

The reasons why the explanatory variables listed in table 5.3.1 were chosen as debt crisis indicator variables are highlighted below. The expected sign of each variable is included in the third column of table 5.3.2:

Indicator Variable	Why it was chosen as an indicator variable	Expected sign
GDP/Capita	Rescheduling of debt is less likely in countries with higher income due to the high costs of rescheduling in higher income countries. The possibility of banking and debt crises is expected to be higher when domestic economic activity is curtailed (Dermirguc-Kunt and Detraigiache, 1998).	(-)
Current account/GDP	The expected result of a rise in this ratio is large capital inflows which the domestic financial system intermediates. This could promote credit and asset price booms (Berg and Patillo, 1999; Lestano, Jacobs and Kuper, 2003). The expectation of an increase in a current account surplus	(-)

	would be a lower chance to devalue which implies a lower chance of a crisis (Lestano, Jacobs and Kuper, 2003).	
Growth in reserves	The total value of foreign reserves is oft used as an indicator of the financial difficulty a country has in dealing with debt repayment (Lestano, Jacobs and Kuper, 2003).	(-)
Investment/GDP	Investment and debt are associated. Often, investments are funded through borrowed funds. Dividing investment by GDP gives the level of investment as a share of GDP.	(+)
Savings/GDP	The probability of debt rescheduling may be expected to be lower when the levels of national saving are higher (Lanoie and Lemarbre, 1996)	(-)
M2	This is an indicator often associated with financial liberalization while draconian abatements in reserve requirements explain vast increases in the money multiplier (Kaminsky et al, 1997; Berg and Patillo, 1999; Edison, 2003; Lestano, Jacobs and Kuper, 2003)	(+)
Terms of trade	The balance of payments position should improve with an increase in terms of trade, thereby lowering the probability of a crisis (Kaminsky et al, 1997; Berg and Patillo, 1999).	(-)
Real GDP	The probability of a crisis occurring is increased when domestic economic activity deteriorates.	(-)
The Spread	Relatively high South African interest rates will decrease domestic borrowing.	(-)
Gold Price	The price of gold tends to increase sharply in times of economic uncertainty, as investors view gold as a safe haven investment. Thus sharp increases in the price of gold are often associated with crises, a phenomenon observed during the recent debt crisis in Europe.	(+)
Oil Price	Higher oil prices and recessions tend to be associated.	(+)

Table 5.3.2 Importance of Debt Crisis Indicators

5.4 The OLS approach

Before proceeding with the Logit and Markov-switching approach, I begin with a simple approach- using OLS to forecast changes in the debt pressure variable, DPV. The OLS approach is the logit approach in a time series context. That is, lagged values of the indicator variables will be used to try and forecast the occurrence of a crisis, but instead of using a binary dependent variable, the continuous DPV variable is used.

The reason that I introduce the OLS approach to forecasting in this paper is because it may be useful to forecast the movements of the debt pressure variable itself. Abiad (1999) points out that the binary transformation used to create the CC_t variable (see equation 5.1.5) results in a loss of information- one only knows whether or not the DPV variable has pierced the boundary or not; one does not know the movements of the DPV variable above or below the boundary. For this reason, it may be useful to create a model that forecasts movements in the DPV variable itself.

The explanatory variables used in this approach can be found in table 5.3.1. The dependent variable is the DPV variable.

5.5 The Logit/Probit Approach

This early warning system model provides the probability of the onset of a crisis, k-periods ahead, conditional on a given set of indicators[24]. Seminal contributions to the logit/probit approach were made by Frankel and Rose (1996). In this approach, the indicators chosen are those which theory suggests might explain a crisis. Lagged values of these indicator variables are used as explanatory variables in order to predict crisis periods. This approach is useful for seeing the extent to which the indicator variables affect crisis probabilities. The dependant variable is the probability of a crisis. This approach requires predetermined crisis periods. A crisis period is defined as a period in which the crisis pressure variable exceeds some threshold. In order to determine whether the pressure for a crisis may be building, it is necessary to measure market pressure.

One is interested in *forecasting* the probability of a crisis. Thus, leads are introduced. To introduce such leads, a new variable Y_t is defined as follows:

[24] The logit/probit model will be explained in greater detail in the methodology section.

$$Yt = \begin{cases} 1\ if\ \exists\ k = 1,2,\ldots,d, s.t., CC_{t+k} > 0\ with\ probability\ \Pr(Y=1) = P \\ 0\ if\ \exists\ k = 1,2,\ldots,d, s.t., CC_t = 0\ with\ probability\ \Pr(Y=0) = 1-P \end{cases} \quad (5.5.1)$$ [25]

Here, d is the time period over which the crisis is to be forecasted. Obviously, there is a trade off involved with the choice of d. If d is low, one is only able to get forecasts a period or two in advance, which may not provide adequate time for policy makers to react. A forecast too far in advance, on the other hand, may come at the expense of accuracy (Fedderke, 2011)

The explanatory variables used for forecasting can be found in table 5.3.1. There are three main advantages of the logit/probit approach. Firstly it produces a simple and easily understood result, the probability of the onset of a crisis, from all the information used. Secondly, a lotgit/probit model can be run on statistical software packages, without any difficulty and the statistical significance of each variable can be evaluated. Finally, the marginal input of each right hand side variable is taken into account, while looking at all the indicators together.

According to Kaminsky, Lizondo and Reinhart (1997) the disadvantages of the logit/ probit approach are: indicators cannot be compared in terms of forecasting performance. Secondly, an indicators marginal effect on the probability is not easily evaluated due to the binary nature of the model. Statistical software packages give the marginal effect of a change in a right hand side variable but these are calculated at the variables mean, making these marginal effects less appealing in the context of early warning system models where one is looking at situations where variables are not close to their mean (Abiad, 1999). The final disadvantage of the logit/probit approach is that a variable may be statistically significant but that does not mean that it is accurate in predicting crises, it is possible that it simply doesn't send many false signals. Abiad (1999) points out that this disadvantage is not particular to the logit/ probit approach and that significance tells us that the variable is useful for prediction regardless.

5.6 Markov-switching

Abiad (1999) points out some weaknesses in the methodology of the signals and logit/probit approaches: First, before estimation can take place, crisis dates are required a priori. Second, the approaches require thresholds and these thresholds are arbitrary. Also, the use of binary variables results in a loss of information. Abiad (1999) also shuns the two approaches for lacking theoretical motivation. Abiad (1999) introduces a different approach – an approaches which uses

[25] Source: Fedderke (2011)

the Markov-switching technique with transition probabilities that vary with time. Abiad (1999) favours Markov-switching models as they are well suited to variables that exhibit dramatic changes. Markov-switching models explicitly recognize how the current regime may affect the future one. They are also more informative that other models- apart from predicting the timing of a crisis, they can also predict the length of a crisis and which factors might end one. A priori information of crisis periods is no longer required, eliminating the need to set arbitrary thresholds.

In the Markov-switching approach, one assumes that there are distinct states; each with distinct behavioral conditions. For the purposes of applying such models to early warning systems, the two states are tranquil and crisis (Fedderke, 2011).

These unobservable states are denoted by the latent variable s_t such that:

$$s_t = \begin{cases} 1 \; for\ a\ crisis\ state \\ 0 \; for\ a\ tranquil\ state \end{cases} \qquad (5.6.1)$$ [26]

y_t is the market pressure variable; it is observable. y_t depends on s_t since the characteristics of y_t change under the different states; that is, the mean and variance differ under each state. The two state Markov chain is

$$y_t \,|\, s_t \overset{iid}{\sim} N(\mu_{st}, \sigma^2_{st}) \qquad (5.6.2)$$

- Conditional on the state, the density of y_t is

$$f\left(y_t \mid s_t\right) = \frac{1}{\sqrt{2\pi}\sigma_{s_t}} \exp\left(\frac{-\left(y_t - \mu_{s_t}\right)^2}{2\sigma^2_{s_t}}\right) \qquad (5.6.3)$$

- The transition probability matrix P_t, that describes the behaviour of the latent variable, is given in equation 5.6.4.

$$P_t = \left[\begin{array}{c|c} \begin{array}{l} p_t^{00} \\ = \Pr\left(s_t = 0 \mid s_{t-1} = 0; x_{t-1}\right) \\ = F\left(x'_{t-1}\beta_0\right) \end{array} & \begin{array}{l} p_t^{01} = \left(1 - p_t^{00}\right) \\ = \Pr\left(s_t = 1 \mid s_{t-1} = 0; x_{t-1}\right) \\ = 1 - F\left(x'_{t-1}\beta_0\right) \end{array} \\ \hline \hline \begin{array}{l} p_t^{10} = \left(1 - p_t^{11}\right) \\ = \Pr\left(s_t = 0 \mid s_{t-1} = 1; x_{t-1}\right) \\ = 1 - F\left(x'_{t-1}\beta_1\right) \end{array} & \begin{array}{l} p_t^{11} \\ = \Pr\left(s_t = 1 \mid s_{t-1} = 1; x_{t-1}\right) \\ = F\left(x'_{t-1}\beta_1\right) \end{array} \end{array}\right] \qquad (5.6.4)$$

- The transitional probabilities follow the logistic distribution (see Fedderke, 2011).

[26] All equations in this subsection can be found in Fedderke (2011)

- The $\sigma's\ \beta's\ \mu's$ are estimated using the expectation maximization (EM) algorithm by Diebold, Lee and Weinbach (1994)
- To generalize the one-period forecast probabilities to n period forecast probabilities the following equation is used:
  $\Pr(crisis\ over\ the\ next\ n\ months) = \Pr(crisis\ over\ next\ 1\ month)^n$ (5.6.5)
- Where the probability of a crisis exceeds some threshold an alarm is signalled. In the literature the threshold is generally set at about 50% (see Schweickert and De Souza (2005)).

Although the Markov-switching approach is not a straight forward as the other approaches to forecasting, it defines a crisis at the same time as it develops the crisis forecast probability (Fedderke, 2011).

6. The Early Warning System Models

In this section, four early warning system models are presented. The predictive performance of each of these models will be tested both in- and out-of-sample in the context of the OLS approach, the Logit approach and the Markov-switching approach. The in-sample period is from 1985-Q2 until 2006-Q1. In order for a crisis period to be indicated in the OLS models, the forecast of the DPV variable needs to rise above 112.13 or fall below -101.41 as these are the upper and lower boundary levels calculated in equation 5.1.5.

The most important criterion for assessing a EWS model is accuracy of the forecast; statistical significance is less of a concern in the assessment of the models. Thus a models predictive performance will be primarily judged on its ability to pick up the 2006-Q3 crisis (the out-of-sample crisis). In the case of the OLS regressions, the RMSE (Root Mean Squared Errors) will also be commented on throughout in order to assist in the comparison of the different models' forecasts.[27] Although it is the out-of-sample forecast that one is interested in, a model that performs well in-sample may still be somewhat insightful; the goodness of fit of each model will

[27] A lower RMSE indicates a better forecast.

also be looked at. The estimated signs of the coefficients as well as their statistical significance will occasionally be commented on.

6.1 Model 1

Frankel and Rose (1996) attempted to forecast the onset of a crisis, one year in advance and the first model presented in this section follows in their footsteps. In model 1, the indicator variables in table 5.3.1 are lagged by four periods to try to forecast crisis periods, one year in advance.

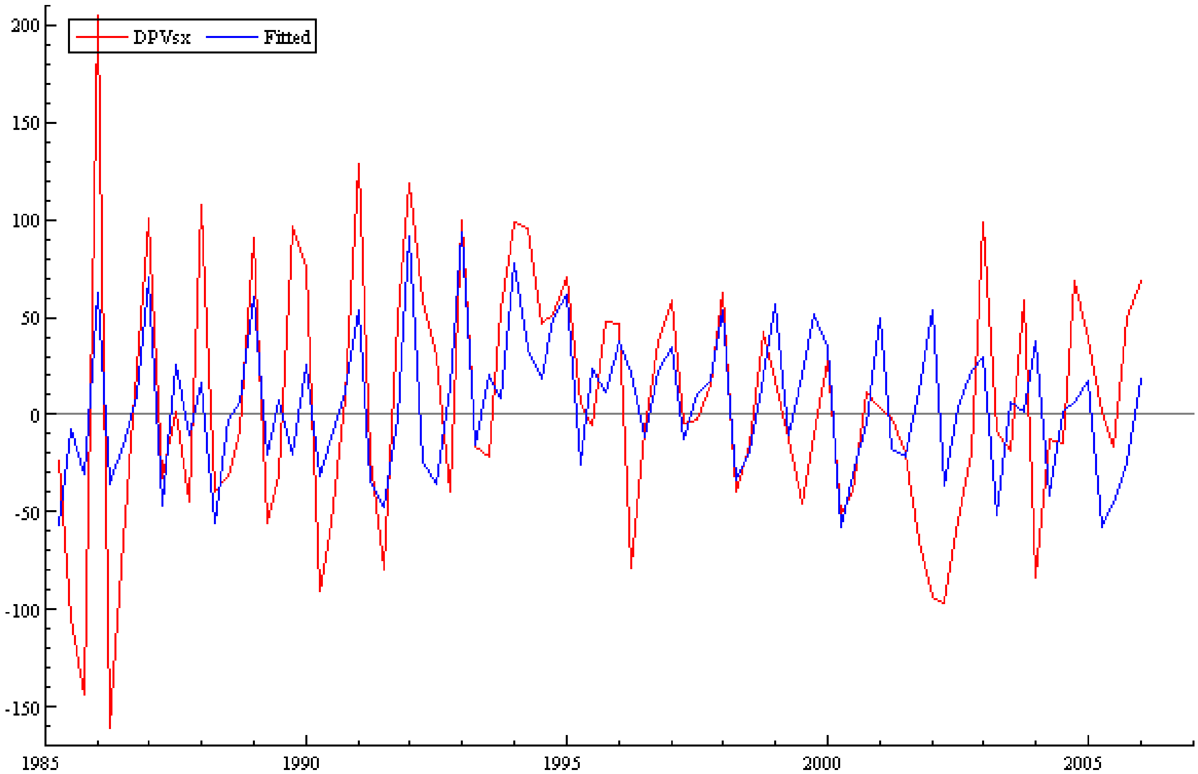
First, I present the in-sample OLS forecast. The dependent variable used for this approach is the continuous debt pressure variable, DPV. The in-sample results are reported below:

The estimation sample is: 1985(2) - 2006(1)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
Constant	261.627	130.1	2.01	0.0481	0.0532
CAGDP_4	0.683871	2.643	0.259	0.7965	0.0009
chgMtwo_4	-1.17462	1.864	-0.630	0.5306	0.0055
ChgSavGDP_4	0.522739	3.221	0.162	0.8715	0.0004
PchgRES_4	-27.6141	25.61	-1.08	0.2845	0.0159
chg GDPcons_4	-0.00264456	0.0009465	-2.79	0.0067	0.0978
ChgTOT_4	-0.338781	2.289	-0.148	0.8828	0.0003
Chg Rsa-Rus_4	-1.85933	6.302	-0.295	0.7688	0.0012
Chg I/GDP_4	2003.81	855.4	2.34	0.0219	0.0708
Chg Ln Oil_4	-66.7402	46.04	-1.45	0.1515	0.0284
Chg Ln Gold_4	113.233	96.55	1.17	0.2448	0.0187
GDPcap_4	-0.0341099	0.01789	-1.91	0.0606	0.0481

sigma	57.6384	RSS	239197.217
R^2	0.311523	F(11,72) =	2.962 [0.003]**
Adj.R^2	0.206339	log-likelihood	-453.268
no. of observations	84	no. of parameters	12
mean(DPVsx)	5.79204	se(DPVsx)	64.6985

The only significant variables, at the 5% level, are the constant, the change in investment as a share of GDP and the change in real GDP. GDP per capita is significant at the 10% level. All of these significant variables have the expected signs. The current account as a share of GDP and the change in savings as a share of GDP have the incorrect signs but these variables are not significant. This in-sample forecast is graphed below:



Graph 6.1.1: The actual and fitted values from the in-sample OLS regression of model 1.

As can be seen from results and graph 6.1.1, model 1 does not perform very well in-sample. With an R^2 of 0.312 it is clear that model 1 has a poor "goodness of fit" rating. None of the in-sample crisis periods are picked up.

The out-of sample forecast results are reported below:

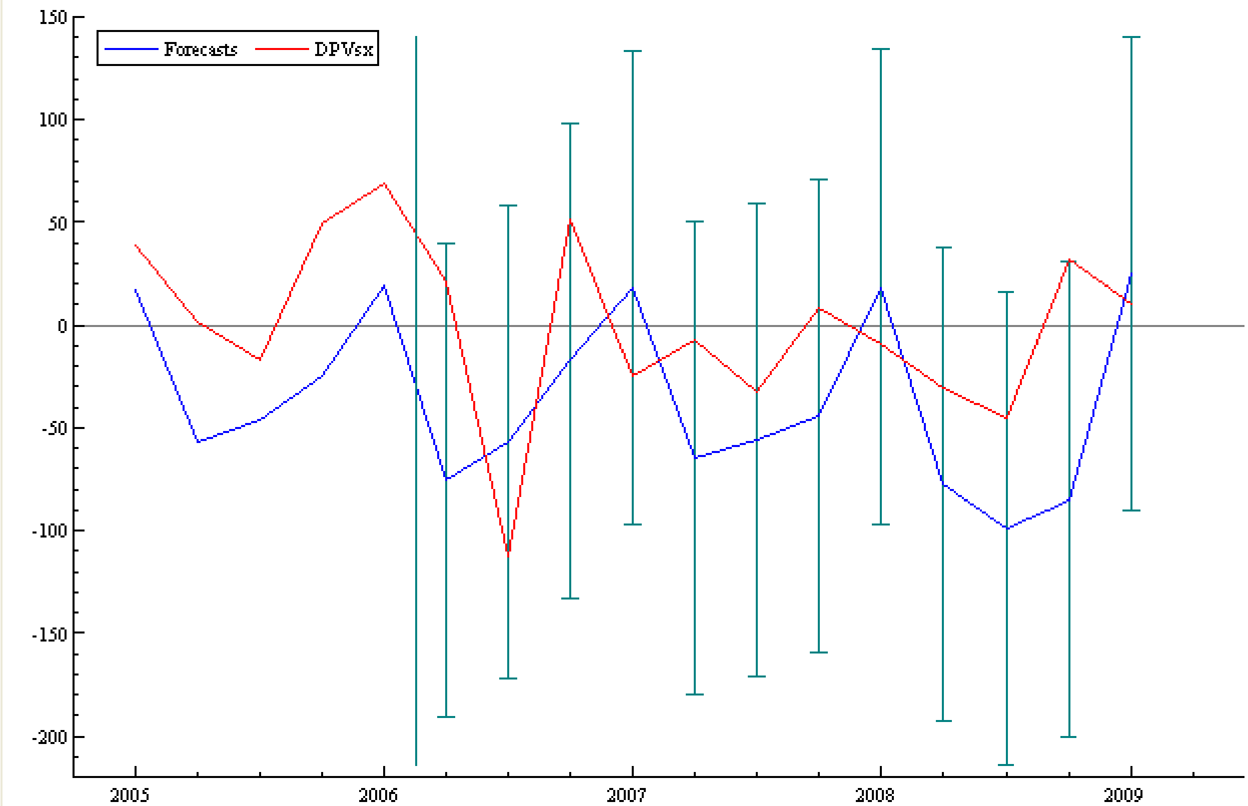
Dynamic (ex ante) forecasts for DPVsx (SE based on error variance only)

Horizon	Forecast	SE	Actual	Error	t-value
2006-2	-75.6077	57.64	20.8714	96.4791	1.674
2006-3	-56.7448	57.64	-112.788	-56.0430	-0.972
2006-4	-17.3004	57.64	51.7160	69.0164	1.197
2007-1	18.2608	57.64	-25.0673	-43.3282	-0.752
2007-2	-64.9601	57.64	-7.11356	57.8465	1.004
2007-3	-56.2217	57.64	-32.8544	23.3673	0.405
2007-4	-44.1903	57.64	8.62940	52.8197	0.916
2008-1	18.6137	57.64	-9.06736	-27.6811	-0.480
2008-2	-77.4371	57.64	-30.1847	47.2524	0.820
2008-3	-98.9199	57.64	-44.9787	53.9413	0.936
2008-4	-84.8607	57.64	32.1290	116.990	2.030
2009-1	24.7642	57.64	10.4960	-14.2682	-0.248

mean(Error) = 31.366 RMSE = 61.624

SD(Error) = 53.045 MAPE = 283.04

The results of the out-of-sample forecast reported above show that model 1 does decrease around the time of the 2006-Q3 crisis but not by enough to pick up the crisis; the DPV would have to decrease below -101.41 to indicate a crisis. The out-of –sample results are graphed below:



Graph 6.1.2: The out-of-sample forecast for model 1 in the OLS regression

Both the written results and the graphical results indicate that model 1 has a poor out-of-sample performance since the 2006-Q3 crisis is not indicated. The forecast does, however, mimic the movements in the DPV to some degree.

Model 1 was tested in the context of a logit model. The indicator variables remain the same as those used in the OLS context. The dependent variable is now the binary crisis period variable, CC. The in-sample results are presented below:

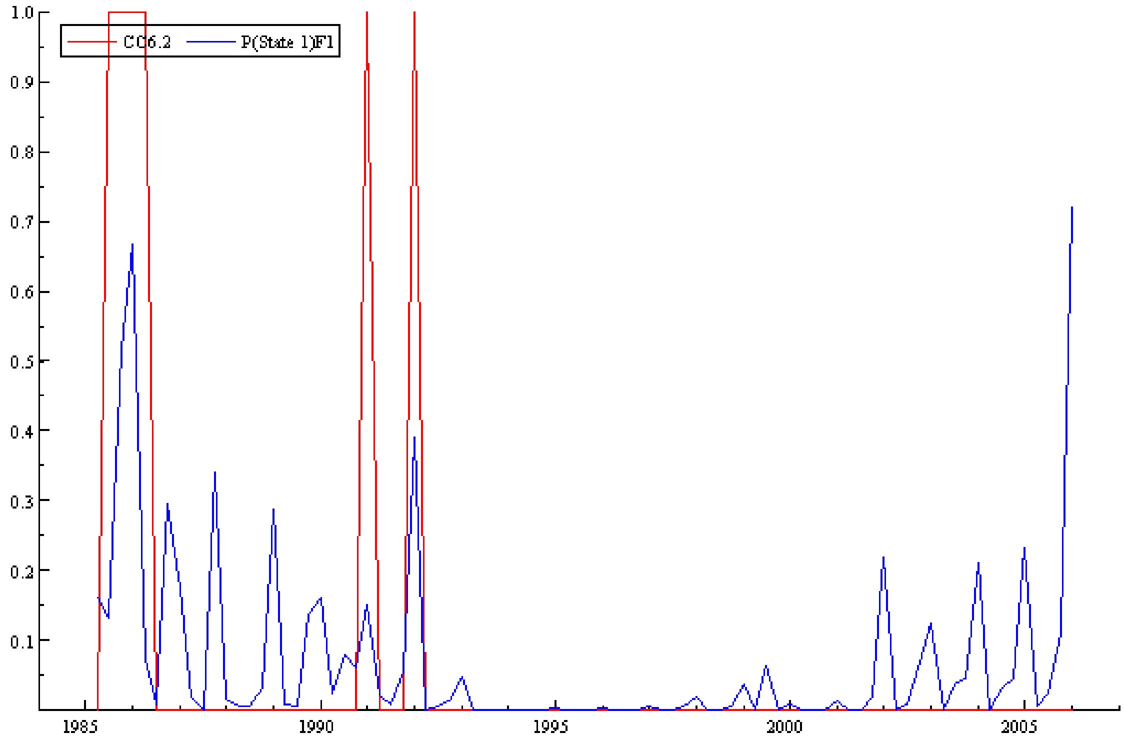
	Coefficient	Std.Error	t-value	t-prob
Constant	-47.8126	20.61	-2.32	0.023
CAGDP_4	0.0317808	0.2608	0.122	0.903
GDPcap_4	0.00598455	0.002692	2.22	0.029
PchgRES_4	-0.308093	2.578	-0.120	0.905
ChgSavGDP_4	0.136549	0.2440	0.560	0.577
chgMtwo_4	-0.0469124	0.1735	-0.270	0.788
ChgTOT_4	-0.177845	0.2048	-0.869	0.388
Chg Ln Oil_4	-2.24024	3.605	-0.621	0.536
Chg Ln Gold_4	-0.369078	8.048	-0.0459	0.964
chg GDPcons_4	-0.000324460	0.0001348	-2.41	0.019
Chg Rsa-Rus_4	0.609790	0.5967	1.02	0.310
Chg I/GDP_4	-24.8334	106.2	-0.234	0.816

log-likelihood	-13.4959513	no. of states	2
no. of observations	84	no. of parameters	12
baseline log-lik	-21.61477	Test: Chi^2(11)	16.238 [0.1325]
AIC	50.9919025	AIC/n	0.607046458
mean(CC6.2)	0.0714286	var(CC6.2)	0.0663265

Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

The significant variables in the logit context are the constant, GDP per capita and the change in real GDP. However, GDP per capita is incorrectly signed; the probability of a crisis should decrease with higher levels of GDP per capita. While the OLS regression yields fitted values corresponding to the DPV, the logit regression gives the probability that a crisis will occur. Crisis periods are referred to as “state 1” in the logit results. The coefficients in the logit regression indicate how the probability of a crisis is affected by a change in the explanatory variables. For example a 1% increase in the growth rate of foreign reserves decreases the probability of a crisis by 0.31%.

The estimated probabilities of a crisis (state 1) from model 1 are graphed against the binary CC variable below. That is, we are graphing the actual crisis dates (dates where thee CC variable is equal to 1) against the estimated crisis dates, predicted by the logit model. This graph gives an indication of how good the logit models in-sample predictive performance is. In the case of the written results, the log-likelihood ratio is used to compare the in-sample forecasts of different logit models.[28]



Graph 6.1.3 The in-sample forecast of model 1 in the logit approach

Using a threshold probability level of 0.35 to indicate a crisis, crises are indicated for 1985-Q4 and 1986-Q1 (corresponding to the major debt crisis that began in in1985-Q3) as well as 1992-Q1. The 1991-Q1 crisis was missed. Also, one false positive is picked up in 2005-Q2.

[28] The model with the best in-sample performance is that with the highest log-likelihood ratio- that is, one is aiming to maximize this ratio if one is looking for a good in-sample fit.

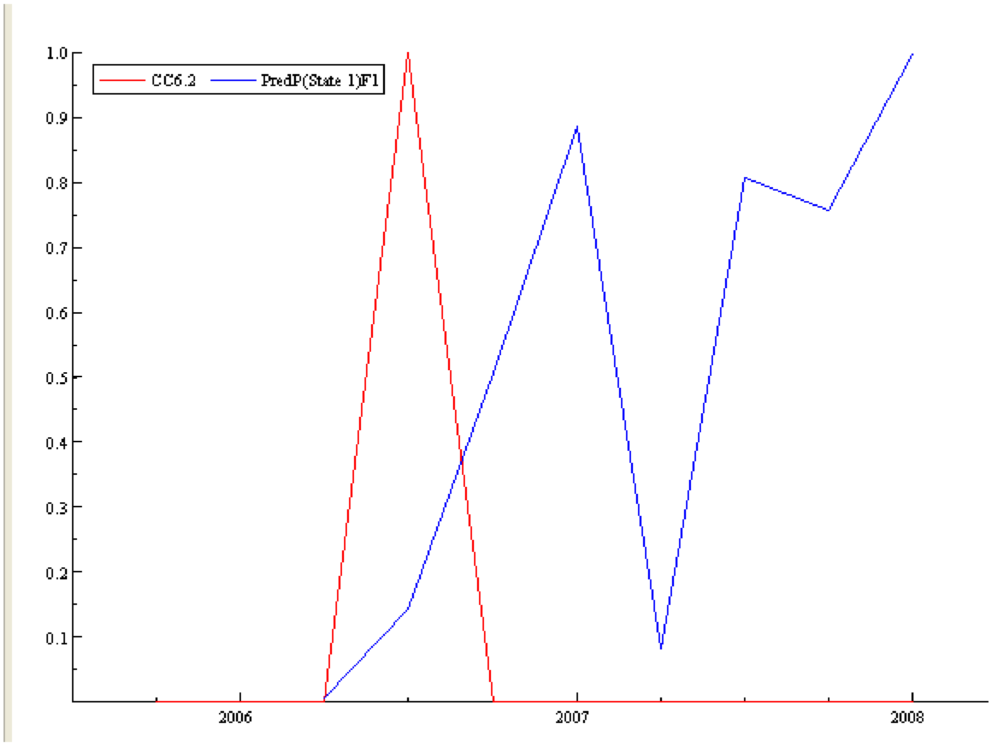
The out-of-sample predictions of the logit model are tabulated below:

index(1)	actual	predicted	State 0	State 1
94	.NaN	0	0.9459	0.05407
95	.NaN	1	0.04238	0.9576
96	.NaN	1	0.4236	0.5764
97	.NaN	0	0.5038	0.4962
98	.NaN	0	0.9872	0.01278
99	.NaN	0	0.8714	0.1286
100	.NaN	0	0.6659	0.3341
101	.NaN	0	0.9404	0.05959
186	0	0	0.9936	0.006400
187	1	0	0.8577	0.1423
188	0	1	0.4939	0.5061
189	0	1	0.1140	0.8860
190	0	0	0.9179	0.08211

Although the logit model does not indicate a crisis in 2006-Q3, it does indicate a crisis for the following two quarters; this may simply be an issue of timing.

Thus, model 1 is more informative than random guessing. In fact, given that model 1 is designed to forecast a crisis one year in advance, this model would have been able to warn policy makers that the pressure for a crisis was coming, three quarters in advance.

The out-of-sample forecast is graphed below:



Graph 6.1.4 The out-of-sample logit forecast of model 1.

6.2 Model 2

Abiad (1999) points out that by lagging all the indicator variables by k periods (whereby k=4 in the case of model 1, for example) one is not taking the effects of the intervening periods into account; the behavior of indicator variables in the periods between t and t+k may also affect the probability of a crisis. Model 2 maps the relationship between the crisis periods indicator (DPV in the case of OLS and CC in the logit context) and the lagged indicator variables. Model 2 is less restrictive than model 1; in this model, the indicator variables may be lagged between 2 periods and 8 periods ahead. I have not used 1 period ahead lags due to the tradeoff mentioned in section 5.5. Recall, a 1 quarter ahead forecast does not give policy makers much time to react. Of course, by only including later lags there is a loss of accuracy in the forecasts.

To arrive at model 2, I began by including all the indicator variables with all the lags, except lag 1. From here I eliminated all the variables that were not statistically significant explanatory variables. The dropped variables were then re-added to the model, one at a time, to see what their effect on the model was. The variables that made the in-sample forecast pick up the in-sample crisis dates were kept in the model; those that were not useful in picking up crisis dates were dropped.

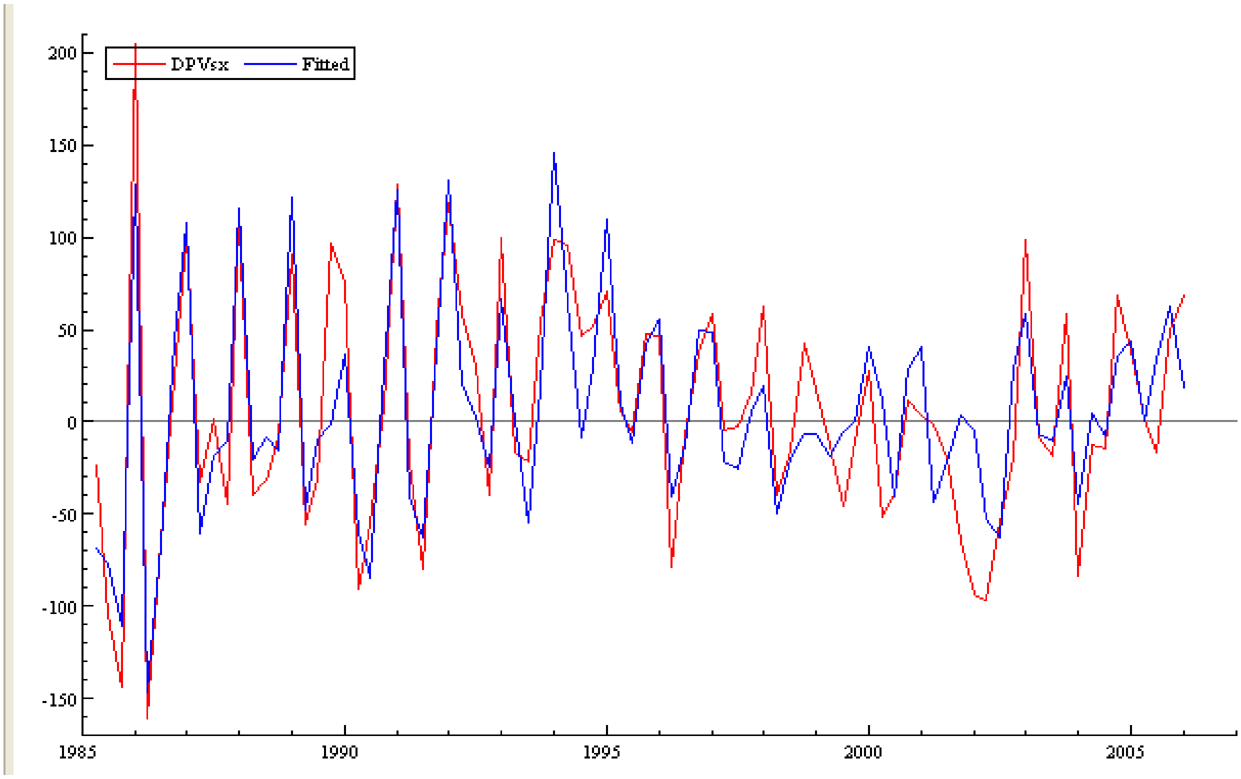
In the OLS context, Model 2 is presented below:

The estimation sample is: 1985(2) - 2006(1)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
CAGDP_8	6.63977	1.864	3.56	0.0007	0.1572
GDPcap_4	-0.906997	0.09997	-9.07	0.0000	0.5476
GDPcap_5	0.504166	0.1096	4.60	0.0000	0.2374
GDPcap_6	0.388646	0.1016	3.82	0.0003	0.1770
ChgSavGDP_8	-5.50490	2.135	-2.58	0.0121	0.0891
chgMtwo_7	-3.21170	1.187	-2.71	0.0086	0.0972
ChgTOT_8	6.33335	1.450	4.37	0.0000	0.2190
chg GDPcons_4	0.0257316	0.003033	8.48	0.0000	0.5142
chg GDPcons_5	0.0121637	0.003128	3.89	0.0002	0.1819
chg GDPcons_7	-0.00397368	0.0006901	-5.76	0.0000	0.3278
chg GDPcons_8	-0.00377858	0.001292	-2.92	0.0047	0.1117
Chg Ln Gold_4	121.150	60.22	2.01	0.0482	0.0562
Constant	61.0884	88.29	0.692	0.4913	0.0070
ChgTOT_6	-3.26527	1.477	-2.21	0.0304	0.0671
Chg Ln Gold_2	-95.7126	60.02	-1.59	0.1154	0.0360
CAGDP_2	-6.18207	1.915	-3.23	0.0019	0.1329

sigma	36.1177	RSS	88705.2342
R^2	0.744681	F(15,68) =	13.22 [0.000]**
Adj.R^2	0.688361	log-likelihood	-411.606
no. of observations	84	no. of parameters	16
mean(DPVsx)	5.79204	se(DPVsx)	64.6985

Model 2 performs well in-sample; an R^2 of 0.745 is indicative of a "good fit". Also, by looking at the graph below, all the in-sample crises periods are picked up (although, the 1985 crisis is picked up from 1985-Q4). Unfortunately, three additional crises are indicated: 1988-Q1, 1989-Q4 and 1994-Q1. It is possible that these false positives are in fact crisis dates that were not indicated due to the construction of the boundaries. All three of these dates correspond to times where the debt pressure variable has spiked, but just misses piecing the upper boundary. That is, these false signals correspond to periods where the pressure for a crisis may be building, but does not rise high enough to indicate a crisis using the definition in equation 5.1.5. In fact, the late 1980s was a period under which South Africa was in a debt standstill. Also, debt rescheduling agreements took place in 1987 and 1989 (as well as 1985, of course). The explanatory variables used in model 2 may be picking up these events.



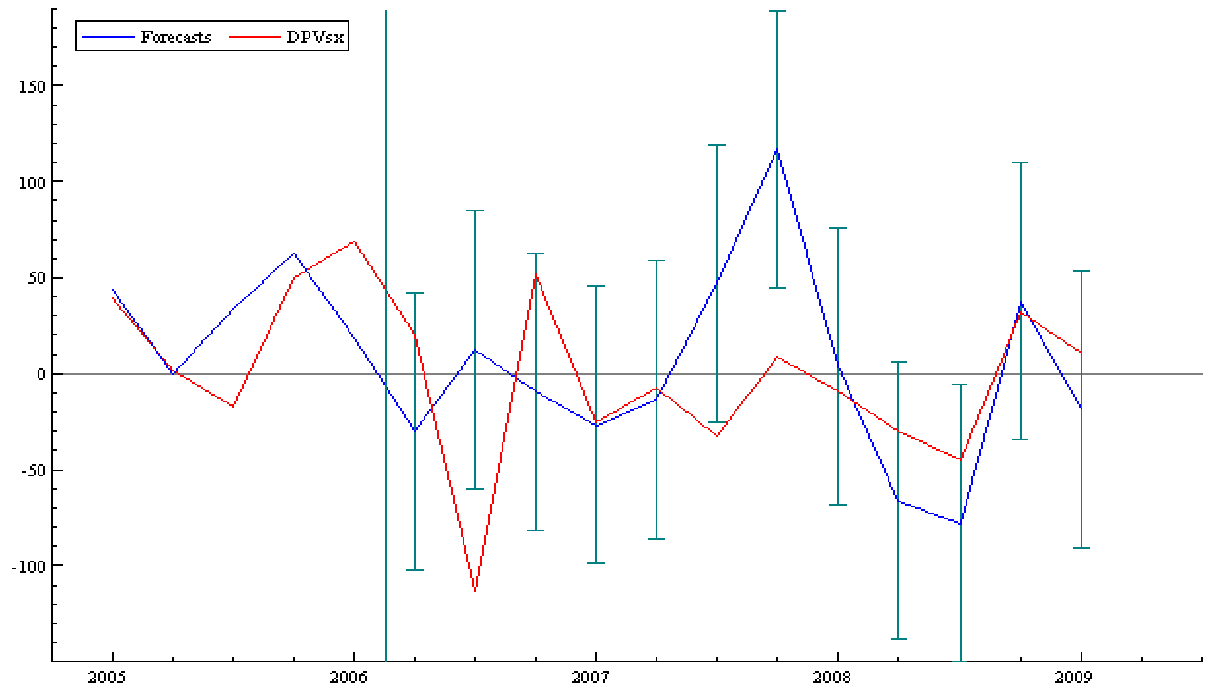
Graph 6.2.1. The in-sample forecast of model 2 using OLS

The out-of-sample forecast of model 2 is presented below:

Dynamic (ex ante) forecasts for DPVsx (SE based on error variance only)

Horizon	Forecast	SE	Actual	Error	t-value
2006-2	-29.9926	36.12	20.8714	50.8640	1.408
2006-3	12.3898	36.12	-112.788	-125.178	-3.466
2006-4	-9.29031	36.12	51.7160	61.0063	1.689
2007-1	-26.6425	36.12	-25.0673	1.57521	0.044
2007-2	-13.6789	36.12	-7.11356	6.56531	0.182
2007-3	46.9075	36.12	-32.8544	-79.7619	-2.208
2007-4	116.832	36.12	8.62940	-108.203	-2.996
2008-1	4.07063	36.12	-9.06736	-13.1380	-0.364
2008-2	-66.1857	36.12	-30.1847	36.0010	0.997
2008-3	-77.7479	36.12	-44.9787	32.7692	0.907
2008-4	37.8410	36.12	32.1290	-5.71202	-0.158
2009-1	-18.3328	36.12	10.4960	28.8288	0.798

mean(Error) = -9.5319 RMSE = 60.208
SD(Error) = 59.449 MAPE = 224.78



Graph 6.2.2 The out-of-sample forecast of model 2 using OLS

Out-of-sample, model 2 does not perform very well; it does not indicate the 2006-Q3 crisis at all and it indicates a crisis in 2007-Q4 (the upper boundary is 112.13 and the forecast for 2007-Q4 is 116.832).

If a crisis is predicted but does not occur it is termed a false alarm (or false positive). Model 2 contains some false alarms both in- and out-of-sample. Such information may be important for the following reasons: Firstly, some situations may not be defined as crises but still require attention. Secondly, good fortunes or actions by policy makers may avert such crises. It is, in any case, better to be warned and nothing happens than to not be warned at all.

However, the forecast of model 2 does follow the DPV quite well. In fact, it even has a lower RMSE than model 1. Therefore, although it misses the 2006-Q3 crisis, model 2 does provide some insight out-of-sample as it indicates the movements in the DPV; even though it does not indicate the magnitude of such changes in the DPV. In-sample model 2 performs quite well; it picks up all of the in-sample crises. Model 2 appears to be particularly sensitive to pressures that are brought about by unsustainably high levels of debt- i.e. crises where the DPV pierces the upper bound. This may explain the difficulty model 2 has in indicating the 2006-Q3 crisis which is due to the contractionary effect of low levels of debt. Thus model 2, in the OLS context, may be a functional tool that policy makers can use for avoiding unsustainably high levels of debt. Of course, given the sensitivity of model 2 to such pressures, judgment will be required in order to have an idea of when to react to such pressures.

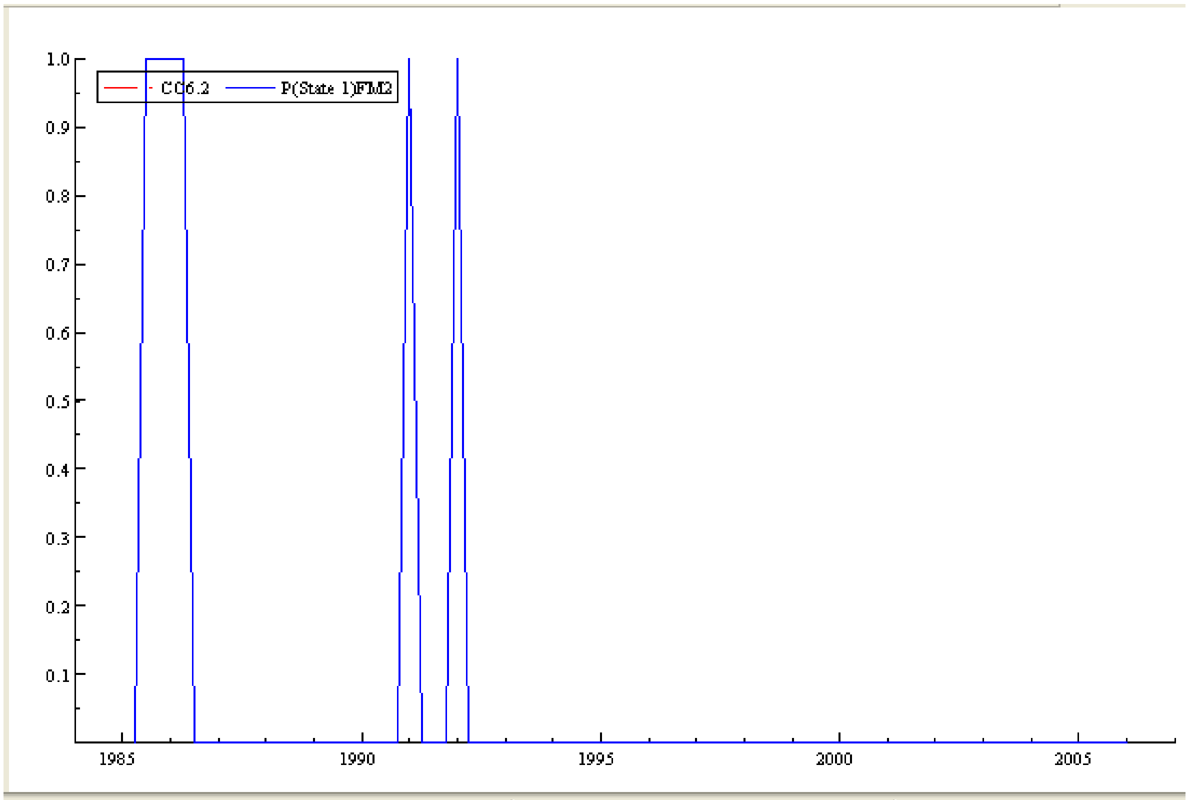
Placing model 2 into the logit context (with CC as the dependent variable rather than DPV) yields the following results:

	Coefficient	Std.Error	t-value	t-prob
Constant	-535.876	6.506e+006	-0.00	1.000
CAGDP_2	7.84498	1.011e+008	0.00	1.000
CAGDP_8	-48.4127	1.499e+008	-0.00	1.000
GDPcap_4	-0.572906	2.016e+006	-0.00	1.000
GDPcap_5	-0.251094	2.727e+006	-0.00	1.000
GDPcap_6	0.865673	1.817e+006	0.00	1.000
ChgSavGDP_8	-24.4918	1.037e+008	-0.00	1.000
chgMtwo_7	-7.43964	8.134e+007	-0.00	1.000
ChgTOT_6	27.2326	8.381e+007	0.00	1.000
ChgTOT_8	-3.79982	4.461e+007	-0.00	1.000
chg GDPcons_4	-0.00374136	6.129e+004	-0.00	1.000
chg GDPcons_5	0.0210384	6.113e+004	0.00	1.000
chg GDPcons_7	-0.000676048	1.424e+004	-0.00	1.000
chg GDPcons_8	0.0135688	4.166e+004	0.00	1.000
Chg Ln Gold_4	122.105	2.122e+007	0.00	1.000
Chg Ln Gold_2	-144.200	3.570e+007	-0.00	1.000

log-likelihood	-7.77156117e-016	no. of states	2
no. of observations	84	no. of parameters	16
baseline log-lik	-21.61477	Test: Chi^2(15)	43.23 [0.0001]**
AIC	32	AIC/n	0.380952381
mean(CC6.2)	0.0714286	var(CC6.2)	0.0663265

Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence

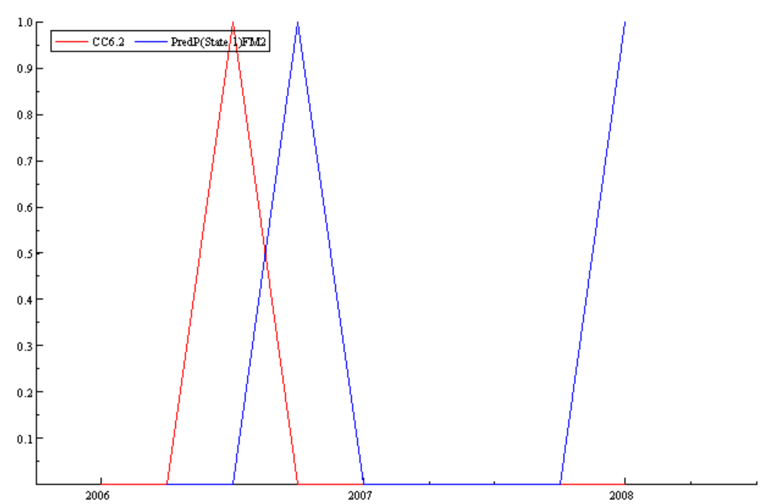
Although the probability that a crisis occurs (state 1) perfectly coincides with the in-sample crisis dates (see graph below), none of the indicator variables are significant in the logit model. However, as already mentioned, one is concerned about the forecast of the EWS model rather than the fit of the model. All but four of the indicator variables are correctly signed. The four incorrectly signed indicator variables are: the current account as a share of GDP (lagged 2 periods), GDP/capita (lagged 6 periods), the change in real GDP (lagged 8 periods) and the change in the terms of trade (lagged 6 periods).



Graph 6.2.3. The in -sample logit forecast of model 2

The out-of-sample results of model 2 are reported below:

index(1)	actual	predicted	State 0	State 1
89	.NaN	0	1.000	4.930e-032
90	.NaN	0	1.000	3.867e-006
91	.NaN	0	1.000	4.930e-032
92	.NaN	0	1.000	6.050e-021
93	.NaN	1	1.779e-010	1.000
94	.NaN	1	4.930e-032	1.000
95	.NaN	1	4.930e-032	1.000
96	.NaN	1	4.930e-032	1.000
97	.NaN	1	4.930e-032	1.000
98	.NaN	1	4.930e-032	1.000
99	.NaN	0	1.000	4.930e-032
100	.NaN	0	1.000	4.930e-032
101	.NaN	0	1.000	4.930e-032
186	0	0	1.000	4.930e-032
187	1	0	1.000	4.930e-032
188	0	1	3.896e-007	1.000
189	0	0	1.000	4.930e-032
190	0	0	1.000	4.930e-032
191	0	0	1.000	4.930e-032
192	0	0	1.000	4.930e-032
193	0	1	4.930e-032	1.000
194	0	0	1.000	4.930e-032
195	0	0	1.000	4.930e-032



Graph 6.2.4 The out-of-sample logit forecast of model 2.

Out-of-sample, the logit model predicts a crisis in 2006-Q4; a quarter later than the 2006-Q3 predetermined crisis date. Again, this may simply be a timing issue. Given that the earliest lag in model 2 is two periods, and that the actual crisis occurred one period earlier than what was predicted, policy makers would still have had a warning, one quarter ahead, that the pressure for a crisis is building. Thus, model 2 is more informative than random guessing.

As a modification, I added the some of the explanatory variables of model 1 to model 2. Specifically, the added variables were the change in the terms of trade (Chg Tot_4), the change in M2 (ChgM2_4) and the ratio of the current account to GDP (CAGDP_4), all lagged four periods. The addition of these variables did not improve the OLS forecasts at all; the out-of-sample forecast remains the same. The addition of these variables does improve the logit out-of-sample forecast, however. Below, I present the out-of-sample logit results of this modified version of model 2.

index(1)	actual	predicted	State 0	State 1
89	.NaN	0	1.000	4.930e-032
90	.NaN	1	4.930e-032	1.000
91	.NaN	0	1.000	4.930e-032
92	.NaN	0	1.000	9.486e-010
93	.NaN	0	1.000	4.930e-032
94	.NaN	1	4.930e-032	1.000
95	.NaN	1	4.930e-032	1.000
96	.NaN	1	4.930e-032	1.000
97	.NaN	1	4.930e-032	1.000
98	.NaN	1	4.930e-032	1.000
99	.NaN	0	1.000	4.930e-032
100	.NaN	0	1.000	4.930e-032
101	.NaN	0	1.000	4.930e-032
186	0	1	4.930e-032	1.000
187	1	1	5.158e-010	1.000
188	0	0	1.000	2.849e-009
189	0	0	1.000	3.101e-028
190	0	1	4.930e-032	1.000
191	0	1	7.417e-013	1.000
192	0	0	1.000	4.930e-032

As can be seen by these results, the 2006-Q3 crisis is picked up. In fact, the model signals that the crisis begins a quarter early. Since this model contains lags that are no sooner than 2 periods ahead, policy makers would have been warned three quarters ahead of the 2006-Q3 crisis that the pressure for a crisis was building.

6.3 Model 3

In creating a EWS model, indicator variables are chosen and their parameters are estimated in order to achieve fitted values that mirror the actual observations in a given sample. Thus, a good in-sample forecast may be somewhat useful. On the other hand, it is also possible that after many different EWS models have been tried, the model with the best in-sample fit may be arrived at by coincidence. Also, over time the factors that affect the likelihood of a crisis occurring may change.

A functional EWS model needs to perform well out-of-sample, after it has been created. That is, it needs to indicate crises in "real time" (Berg, Borenztein and Patillo, 2004).

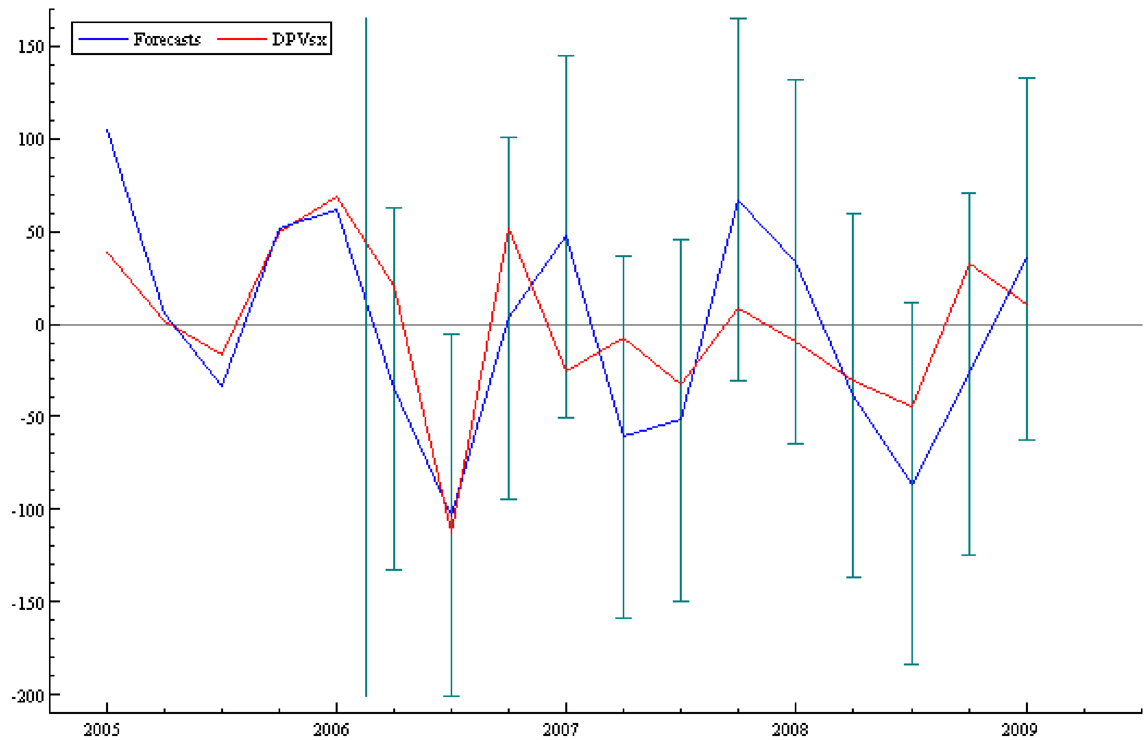
Model 3 is a modification of model 2 whereby indicator variables are added that may improve the out-of sample performance of the model, in the OLS context. Model three is presented below:

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
GDPcap_4	-0.0714952	0.03019	-2.37	0.0211	0.0855
GDPcap_6	0.0734000	0.03065	2.39	0.0198	0.0872
ChgSavGDP_8	-4.24096	3.091	-1.37	0.1751	0.0304
chgMtwo_7	-1.13213	1.973	-0.574	0.5683	0.0055
ChgTOT_8	2.98138	2.160	1.38	0.1726	0.0308
chg GDPcons_4	0.00210888	0.001922	1.10	0.2770	0.0197
chg GDPcons_7	-0.00290897	0.0009294	-3.13	0.0027	0.1404
chg GDPcons_8	-0.00514689	0.001968	-2.61	0.0113	0.1023
PchgRES_4	-35.7331	22.98	-1.55	0.1253	0.0387
PchgRES_8	-51.3098	23.51	-2.18	0.0330	0.0735
Chg Rsa-Rus_6	-13.6162	6.667	-2.04	0.0455	0.0650
mtwo_6	0.866862	0.9469	0.915	0.3636	0.0138
ChgSavGDP_3	4.06980	4.175	0.975	0.3336	0.0156
Chg Ln Oil_1	62.3976	42.31	1.47	0.1455	0.0350
Chg Ln Oil_8	-98.7384	39.24	-2.52	0.0146	0.0955
Chg Ln Oil_4	-79.3401	44.03	-1.80	0.0766	0.0513
Chg Ln Gold_2	-61.2935	95.72	-0.640	0.5244	0.0068
CAGDP_3	-6.39193	4.825	-1.32	0.1903	0.0284
CAGDP_4	2.67700	4.808	0.557	0.5798	0.0051
CAGDP_6	-3.87128	3.984	-0.972	0.3350	0.0155
Chg I/GDP_5	508.584	851.6	0.597	0.5526	0.0059
CAGDP_8	3.95611	3.281	1.21	0.2327	0.0237

CAGDP_2	1.52741	3.793	0.403	0.6886	0.0027
ChgTOT_6	-2.64176	2.200	-1.20	0.2346	0.0235

sigma	48.9009	RSS	143478.081
log-likelihood	-431.802		
no. of observations	84	no. of parameters	24
mean(DPVsx)	5.79204	se(DPVsx)	64.6985

Model 3's out-of-sample performance is satisfactory. It picks up the 2006-Q3 crisis and indicates no other crises between 2006-Q1 and 2009-Q1. This can be seen in the graph below.



Graph 6.3.1. The out-of-sample forecast of model 3 in the OLS context

Model 3 performs better out-of-sample than model 1 and model 2. The results of model 3'sout-of-sample forecast include a root mean squared error (RMSE) of 45.725 while model 1's RMSE was 61.624 and model 2's RMSE was 60.208.[29]

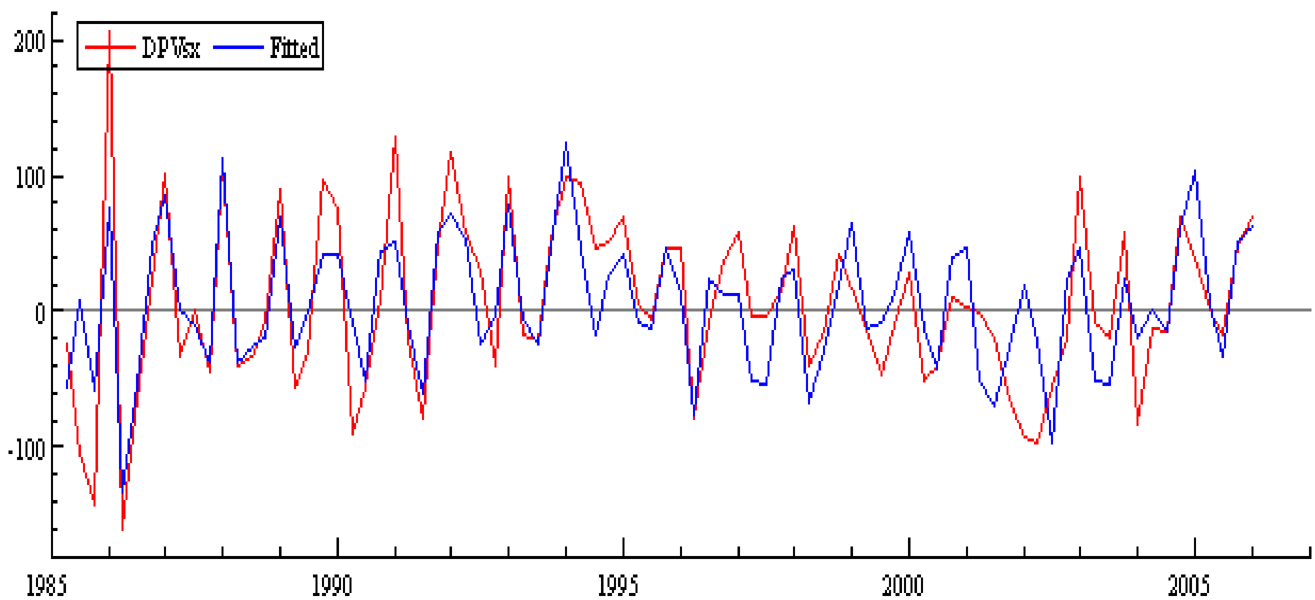
[29] Note, a lower RMSE indicates a better fit.

Dynamic (ex ante) forecasts for DPVsx (SE based on error variance only)

Horizon	Forecast	SE	Actual	Error	t-value
2006-2	-34.6698	48.90	20.8714	55.5412	1.136
2006-3	-103.163	48.90	-112.788	-9.62435	-0.197
2006-4	3.19055	48.90	51.7160	48.5255	0.992
2007-1	47.3023	48.90	-25.0673	-72.3696	-1.480
2007-2	-60.8428	48.90	-7.11356	53.7293	1.099
2007-3	-51.8995	48.90	-32.8544	19.0452	0.389
2007-4	67.0495	48.90	8.62940	-58.4201	-1.195
2008-1	33.4878	48.90	-9.06736	-42.5551	-0.870
2008-2	-38.5362	48.90	-30.1847	8.35149	0.171
2008-3	-86.2881	48.90	-44.9787	41.3095	0.845
2008-4	-26.8544	48.90	32.1290	58.9835	1.206
2009-1	35.4116	48.90	10.4960	-24.9156	-0.510

mean(Error) = 6.4667 RMSE = 45.752
SD(Error) = 45.293 MAPE = 263.10

The in-sample performance of model 3 is less satisfactory than model 2. As can be seen by the graph below, only one of the six in-sample crises is picked up- 1986-Q2. Adding the variable, GDPcon_5 (i.e. the change in real GDP, lag 5) improves the in-sample forecast but also drastically worsens the out-of –sample forecast. The results of model 3 with the addition of GDPcon_5 are inserted into the appendix.



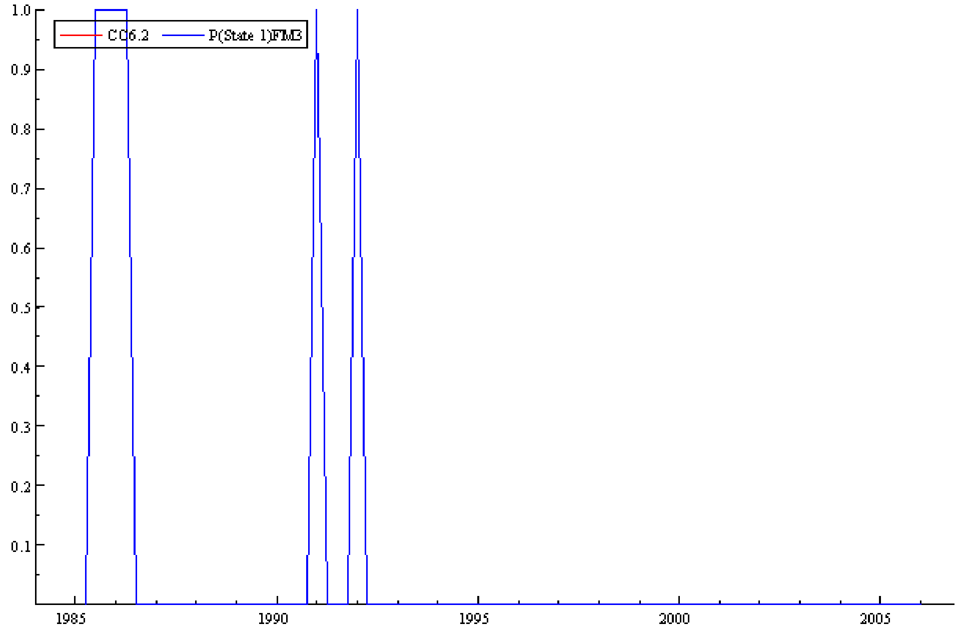
Graph 6.3.2 The in-sample forecast of model 3, in the OLS context.

Model 3 was inserted into the logit context and the results are presented below. Again, the probability of a crisis occurring is equal to one during the predetermined crisis dates. However, like model 2, none of the indicator variables are significant; but, as already mentioned, one is less concerned about significance and more concerned about forecast in the context of Early Warning Systems. The results of the logit model are tabulated below:

	Coefficient	Std.Error	t-value	t-prob
CAGDP_2	22.6056	8.438e+008	0.00	1.000
CAGDP_8	-6.71315	5.554e+008	-0.00	1.000
GDPcap_4	-0.00211807	4.081e+006	-0.00	1.000
GDPcap_6	-0.0130626	4.089e+006	-0.00	1.000
ChgSavGDP_8	-10.7254	5.670e+008	-0.00	1.000
chgMtwo_7	-6.91341	4.240e+008	-0.00	1.000
ChgTOT_6	7.05527	2.974e+008	0.00	1.000
ChgTOT_8	-5.39586	3.749e+008	-0.00	1.000
chg GDPcons_4	-0.00593390	1.982e+005	-0.00	1.000
chg GDPcons_7	0.00370812	1.192e+005	0.00	1.000
chg GDPcons_8	0.00485348	2.322e+005	0.00	1.000
Chg Ln Gold_2	-223.202	1.674e+009	-0.00	1.000
CAGDP_4	-15.5016	5.555e+008	-0.00	1.000
ChgTOT_4	-9.65950	2.907e+008	-0.00	1.000
CAGDP_3	12.0974	8.843e+008	0.00	1.000
CAGDP_6	-7.68902	1.310e+009	-0.00	1.000
PchgRES_4	-48.6814	1.151e+009	-0.00	1.000
PchgRES_8	-3.98813	2.588e+009	-0.00	1.000
Chg Rsa-Rus_6	12.5245	8.171e+008	0.00	1.000
chgMtwo_6	1.08716	3.861e+008	0.00	1.000
ChgSavGDP_3	-16.8066	6.603e+008	-0.00	1.000
Chg Ln Oil_1	79.5250	3.791e+009	0.00	1.000
Chg Ln Oil_4	-42.5672	2.565e+009	-0.00	1.000
Chg Ln Oil_4	-42.5672	2.565e+009	-0.00	1.000
Chg Ln Oil_8	91.7096	2.655e+009	0.00	1.000
Chg I/GDP_5	4946.53	1.281e+008	0.00	1.000

log-likelihood	0	no. of states	2	
no. of observations	84	no. of parameters	25	
zeroline log-lik	-58.22436	Test: Chi^2(25)	116.45	[0.0000]**
AIC	50	AIC/n	0.595238095	
mean(CC6.2)	0.0714286	var(CC6.2)	0.0663265	

Newton estimation (eps1=0.0001; eps2=0.005): Strong convergence



Graph 6.3.3 The in-sample logit forecast of model 3

Out-of-sample, the logit model does not forecast the 2006-Q3 model. Unlike model 2, no crises are forecasted for 2006:

index(1)	actual	predicted	State 0	State 1
96	.NaN	0	1.000	1.267e-024
97	.NaN	1	4.930e-032	1.000
98	.NaN	0	1.000	4.504e-021
99	.NaN	0	1.000	4.930e-032
100	.NaN	0	1.000	4.930e-032
101	.NaN	0	1.000	4.930e-032
186	0	0	1.000	4.930e-032
187	1	0	1.000	4.930e-032
188	0	0	1.000	4.930e-032
189	0	0	1.000	4.930e-032
190	0	0	1.000	4.930e-032
191	0	0	1.000	4.930e-032
192	0	0	1.000	4.930e-032
193	0	0	1.000	4.930e-032
194	0	0	1.000	4.930e-032
195	0	0	1.000	4.930e-032
196	0	0	1.000	4.930e-032
197	0	0	1.000	4.930e-032
198	0	0	1.000	4.930e-032
199	0	1	4.930e-032	1.000
200	0	0	1.000	3.150e-020
201	0	1	4.930e-032	1.000
202	0	0	1.000	9.460e-011

From the above models, I am able to get two models that forecast well out-of-sample in the logit context and one model that forecasts the 2006-Q3 crisis straight from the DPV variable. To be specific, these models are: model 1 logit, model 2 logit and model 3 OLS. Rather than following the forecasts of all three models together, the models should be taken as informative tools for predicting crisis; interpreting the results of the forecasts of each model should be combined with judgment.

6.4 Markov-switching Models

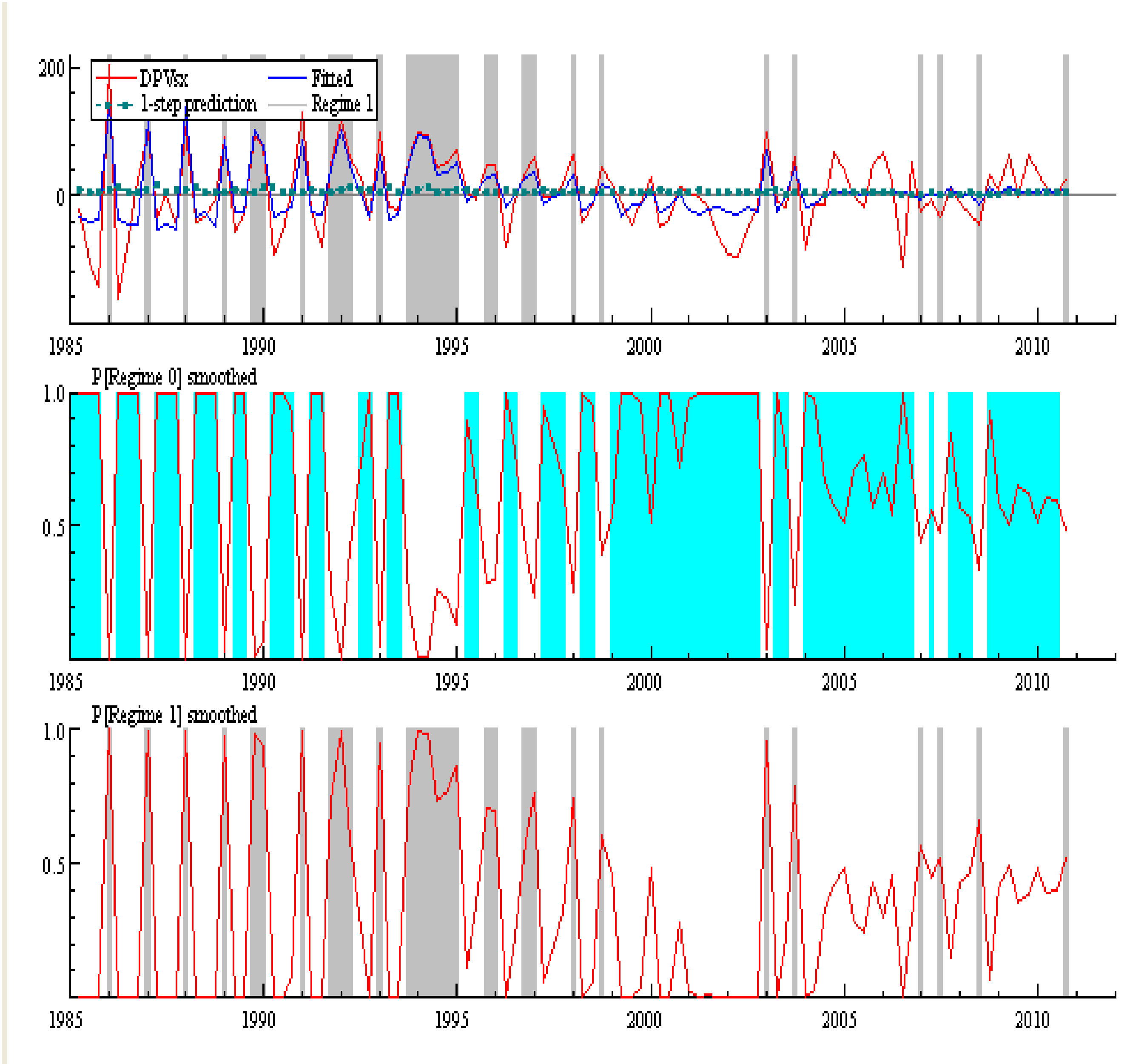
In creating a Markov-switching model, I follow the procedure in Abiad (2003); which begins with a general to specific procedure to reduce the potential number of explanatory variables. This is done by estimating bivariate models; that is, a separate model was run for each explanatory variable (the PCGive results for this regression can be found in the appendix to this paper).

The “hill-climbing” method, that maximum likelihood estimation requires, will converge sluggishly if the indicators have different magnitudes. Abiad suggests transforming each indicator to have zero mean and unit variance. Instead, this paper will transform the indicators into percentage changes, as suggested by Kaminsky, Lizondo and Reinhart (1997) and Berg and Patillo (1999).

Using the bivariate regression results, indicator variables are chosen. Abiad (2003) chose indicators that are correctly signed, while Kittelman et al (2006) chose indicators based on significance and log-likelihood ratios. Following Kittelman et al’s approach, the indicator variables used in this Markov-switching model are the ratio of the current account to GDP and the percentage change in Real GDP.[30] These indicator variables are put into a multivariate regime switching model. The PCGive output for this model can be found in the appendix.

The model’s forecasted probability is then converted into a binary alarm signal, This is done, as usual, by setting a threshold level whereby if the forecast probability exceeds this level, a crisis is signaled. Here, the threshold is set at 50%. The graphs relating to this model are presented below:

[30] This variable was constructed using the same data as the change in real GDP (GDPcon). See table 5.3.1

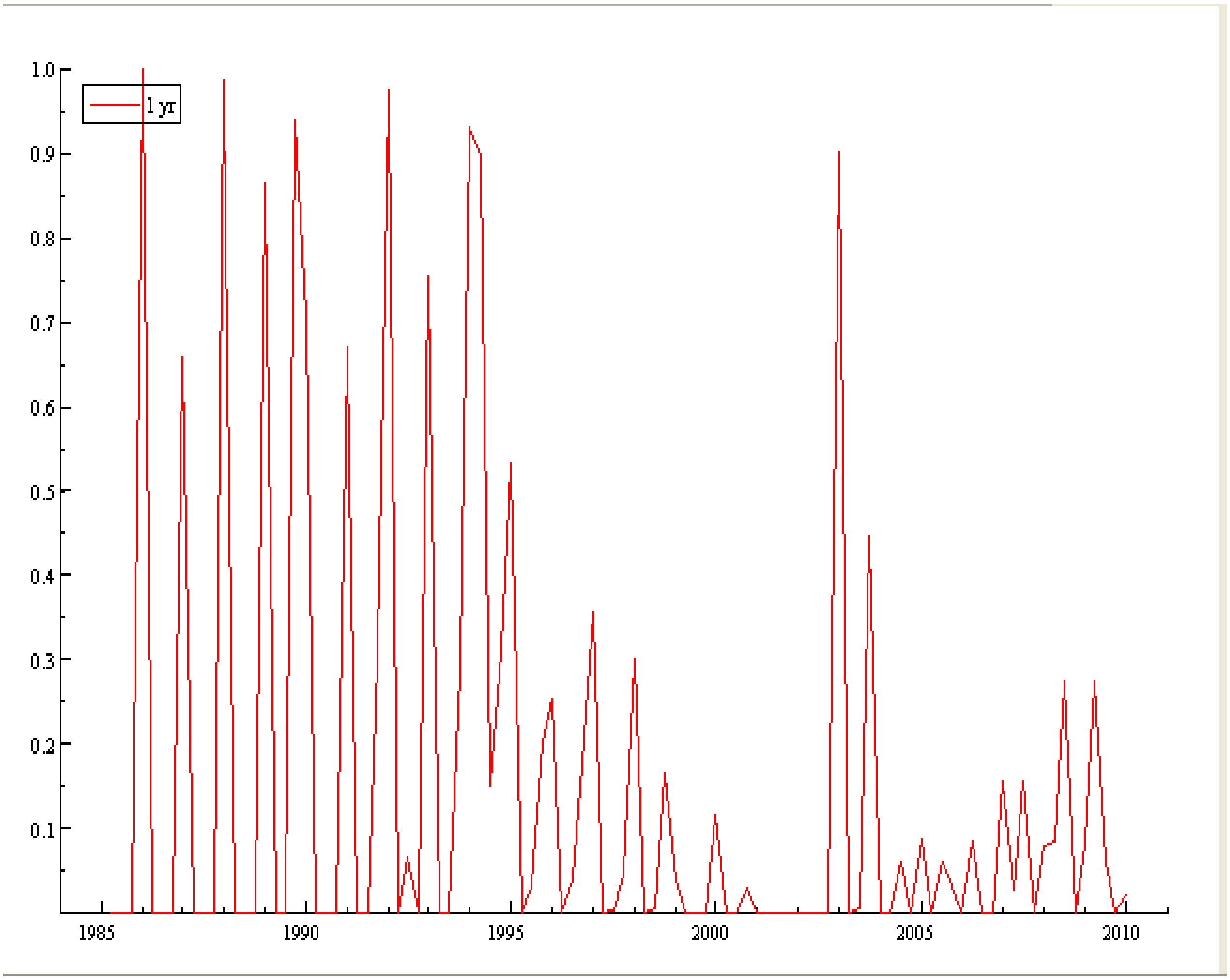


Graph 6.4.1: Graphs indicting the actual and fitted values of the Markov-switching model (first panel), the tranquil periods (second panel) and the periods where the predicted probability is greater than 50% - indicating a crisis (last panel).

The Markov-switching model yields a one period ahead forecast. Thus, to make it comparable, with other EWS models that use longer forecasting horizons, the forecasting horizons must be matched. Assuming that there is no improvement or worsening in the determinants of the crisis probability, this is done using a generalized version of equation 5.6.5:[31]

$$\Pr\text{ (crisis over next n periods)} = \Pr\text{ (crisis over next period)}^{n} \quad (6.4.1)$$

Converting the one quarter ahead forecast to a four quarter ahead forecast yields the following predicted probabilities:

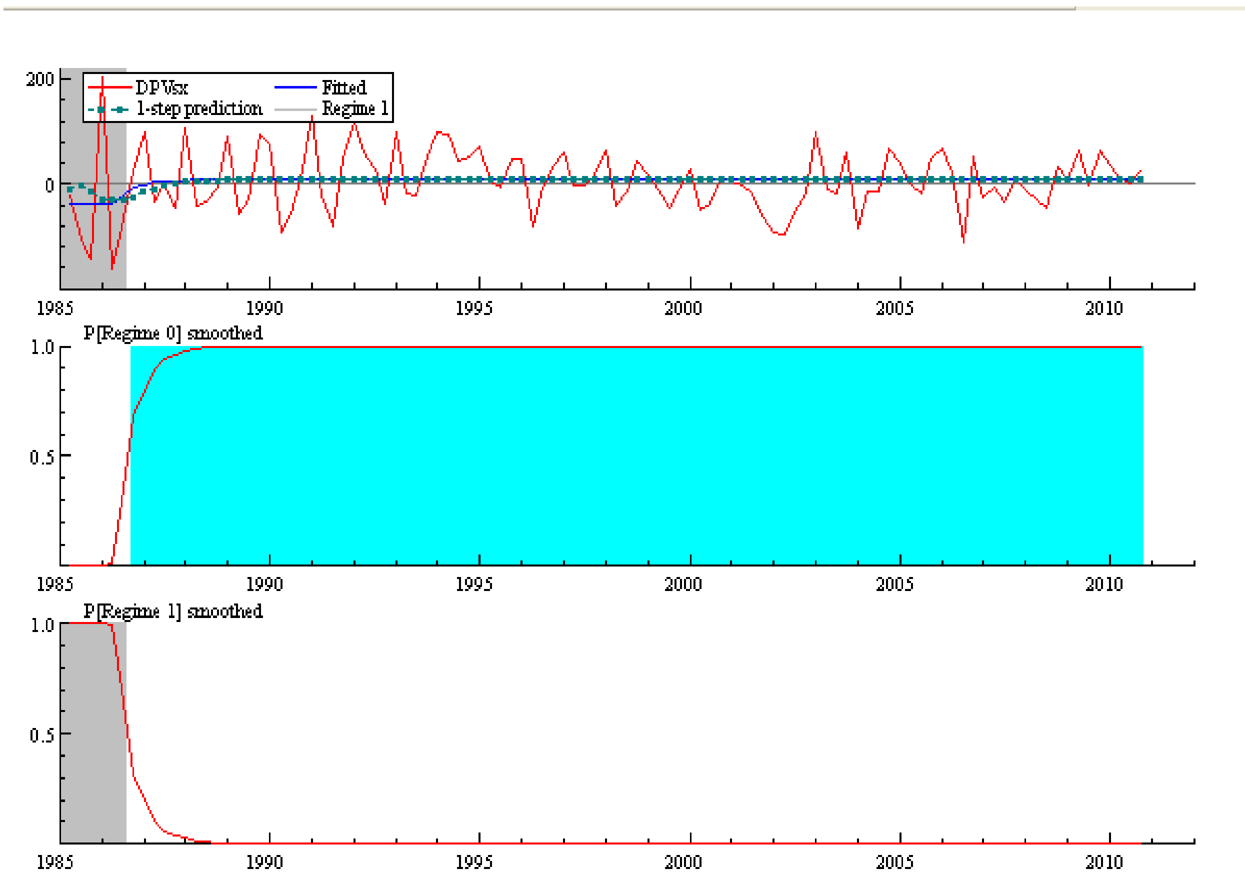


Graph 6.4.2: Four quarter ahead forecast using Markov-switching with only two explanatory variables and the constant.

[31] Note: I have generalized equation 5.6.5 to fit any frequency of data, rather than focusing on monthly forecasts.

The 1986-Q1, 1991-Q1 and 1992-Q1 crises are picked up. Unfortunately, numerous false signals are also indicated. However, although these false positives correspond to periods where, due to the crisis definition used in this paper, are not classified as crises, they are periods in which the debt pressure variable DPV spikes up toward the boundaries. In fact, if the boundary used in defining crisis periods was calculated using 1.5 standard deviations added to the mean rather than 1.75 standard deviations added to the mean, numerous crisis dated would have been indicated between 1985 and 1995, after which no crises occurs until 2002 (see graph 5.2.1, second panel). These results somewhat mirror those of the four period ahead Markov-switching model.

For comparative purposes, Abiad (2003) introduces a baseline model: a simple Markov-switching model with constant transition probabilities; that is, a model with a constant and no explanatory variables. The results of this PCGive output of this model can be found in the appendix. The relevant graphs are presented below:



Graph 6.4.3: Markov-switching model, constant transition probabilities.

As can be seen from graph 6.4.3, the baseline model is only able to pick up the 1985-1986 crisis. However, the duration of the crisis according to this Markov-switching model is longer than the crisis definition of this paper suggests; the Markov-switching model indicates that the crisis begins in 1985-Q2 while the crisis definition used in this paper suggests that it starts in 1985-Q3. From the PCGive output of this baseline model, it is clear that state 0 is a low volatility regime while state 1 is a high volatility regime.

Although this simple model does not pick up all the false positives that the multivariate model indicates, it also does not contain any explanatory variables, which defeats the purpose of an EWS model. Thus, I remind the reader that this simple baseline model is included for comparative purposes and is not considered as an EWS model.

7. Graphical Analysis

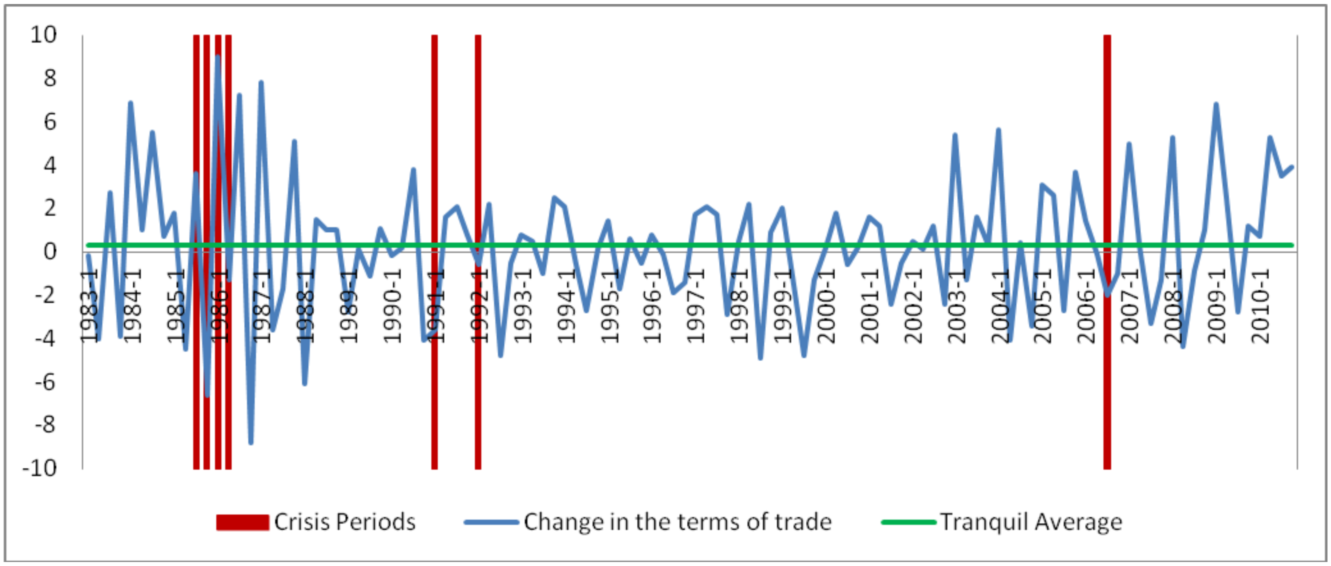
In light of the Event Study Analyses conducted by Frankel and Rose (1996) and Eichengreen et al (1995), a brief graphical analysis is provided in this section.

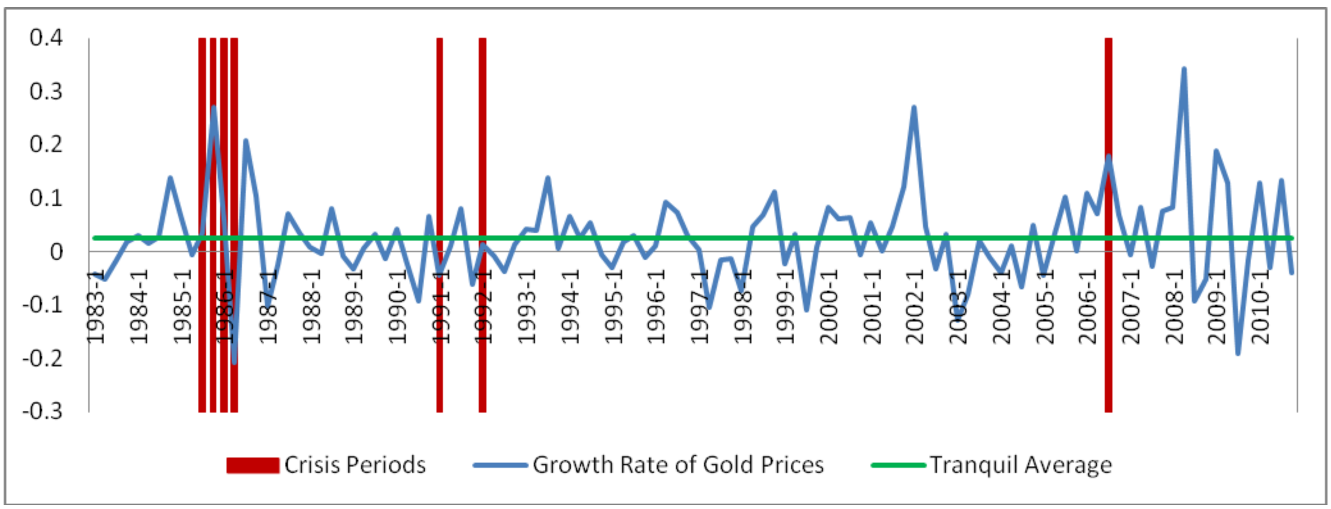
A graphical analysis is used in the Early Warning System literature as it is a helpful method of analyzing the behavior of explanatory variables around crisis periods. It aids one in examining both the "seeds" and the "aftermath" of a crisis (Frankel and Rose, 1996, pp 359).

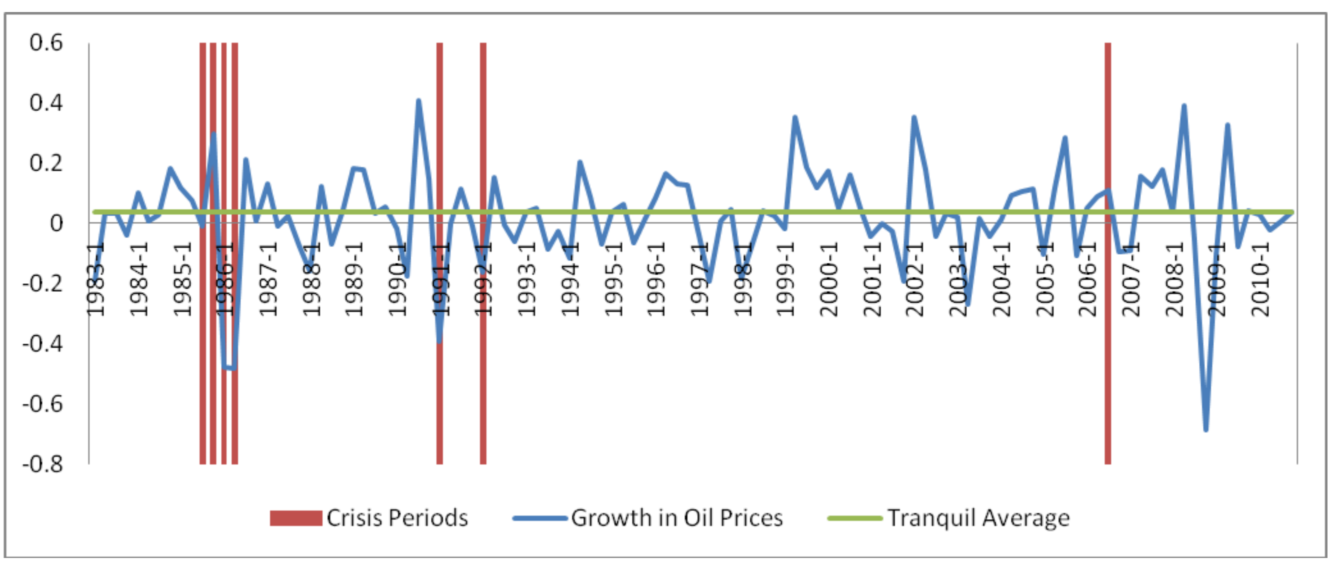
The graphs of each indicator variable are plotted below. Included in each graph are vertical lines representing the predetermined crisis dates. The horizontal line found on each graph represents the mean value of the variable during tranquil periods. Tranquil averages are included in each graphic as they facilitate the comparison of behavior during tranquil periods with that around crisis periods.

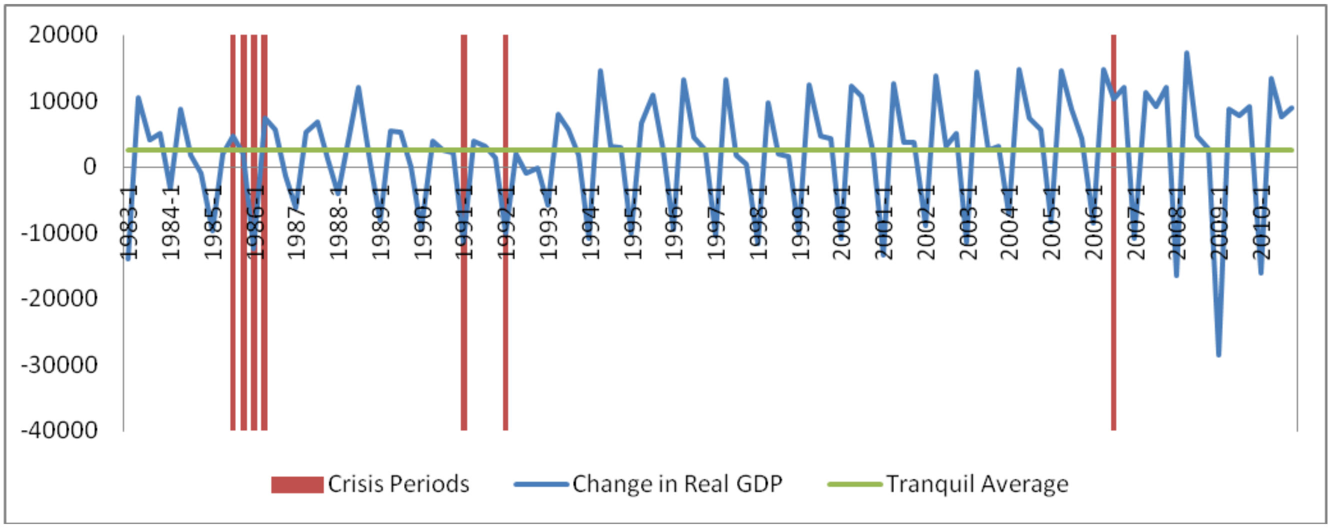
By looking at each graphic, one can see how the indicator variable behaves before, during and after a crisis. In this graphical analysis, all the crisis periods are included in each graphic. This allows one to look at the behavior of each indicator around all the crisis periods in order to see if there is any behavior, of an indicator, that is common to all the crises.

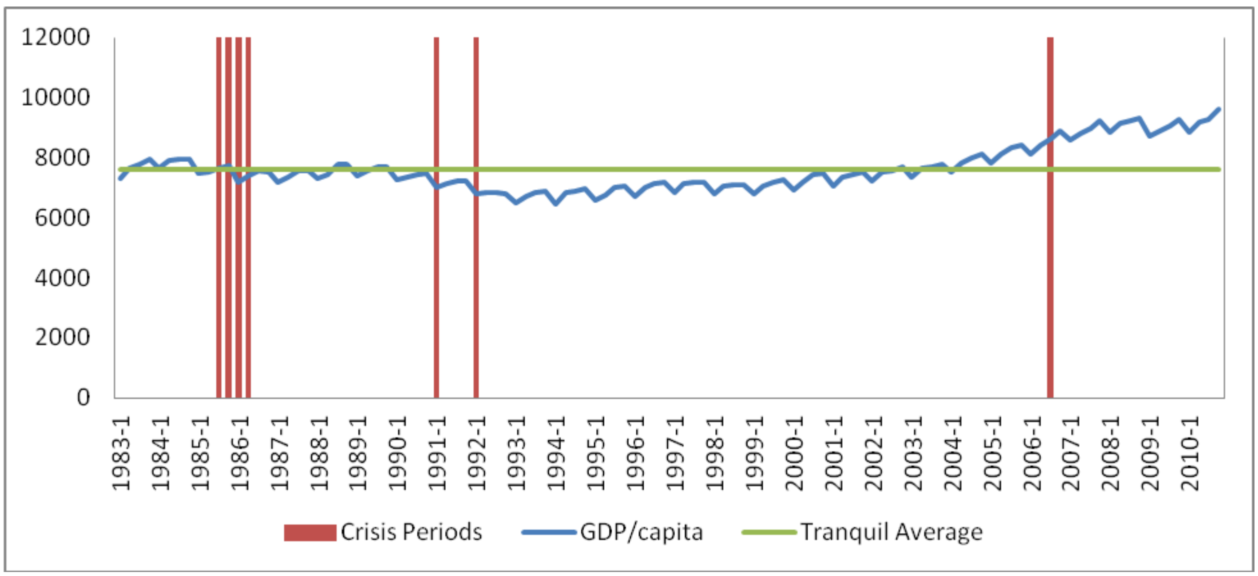
Based on the graphs below, Table 7.1 tabulates the behavior of the indicator variables during the crisis periods.


Crisis Periods
Change in the terms of trade
Tranquil Average


Crisis Periods
Growth Rate of Gold Prices
Tranquil Average


Crisis Periods
Growth in Oil Prices
Tranquil Average


20000
10000
0
-10000
-20000
-30000
-40000
1983-1
1984-1
1985-1
1986-1
1987-1
1988-1
1989-1
1990-1
1991-1
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
Crisis Periods
Change in Real GDP
Tranquil Average


12000
10000
8000
6000
4000
2000
0
1983-1
1984-1
1985-1
1986-1
1987-1
1988-1
1989-1
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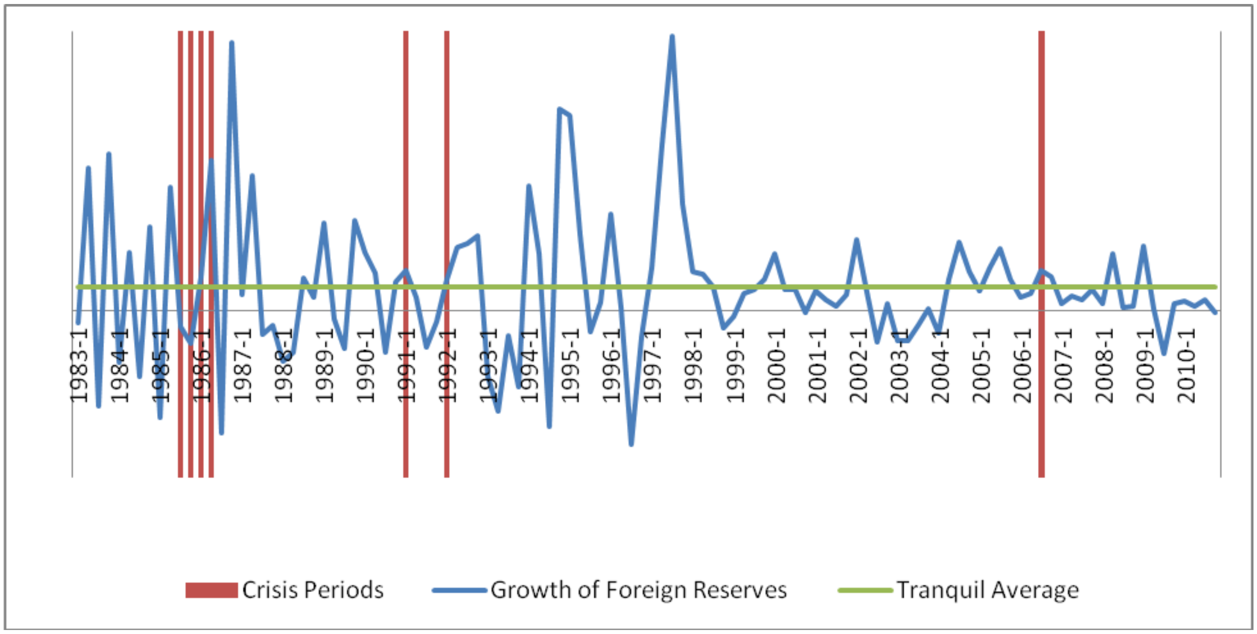
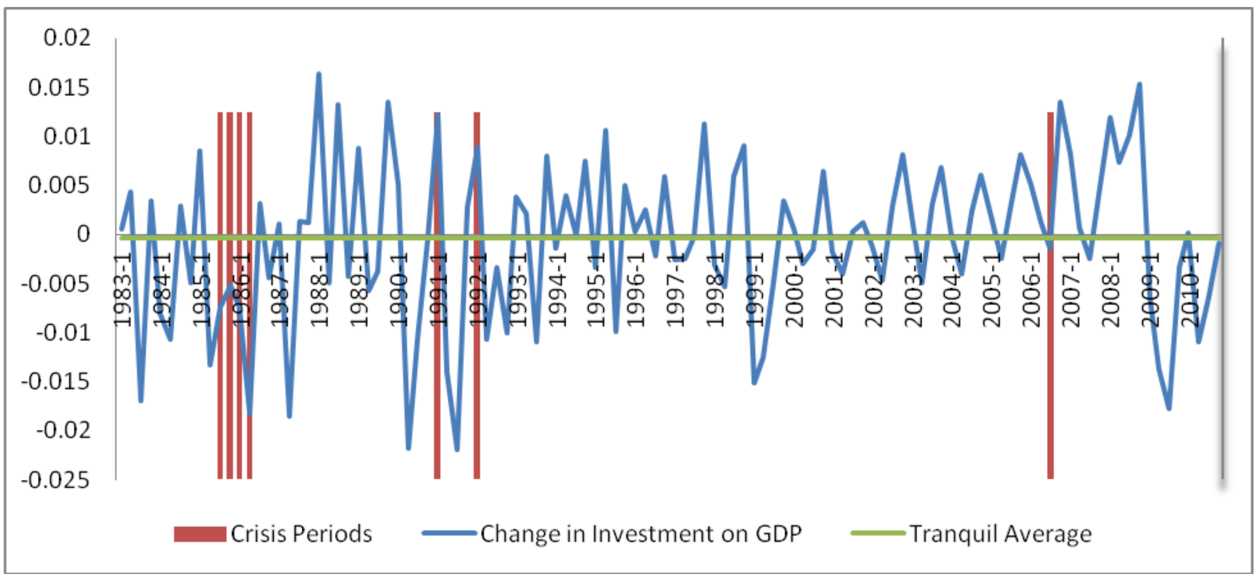
1991-1
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
Crisis Periods
GDP/capita
Tranquil Average


1983-1
1984-1
1985-1
1986-1
1987-1
1988-1
1989-1
1990-1
1991-1
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
Crisis Periods
Growth of Foreign Reserves
Tranquil Average


0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
-0.025
1983-1
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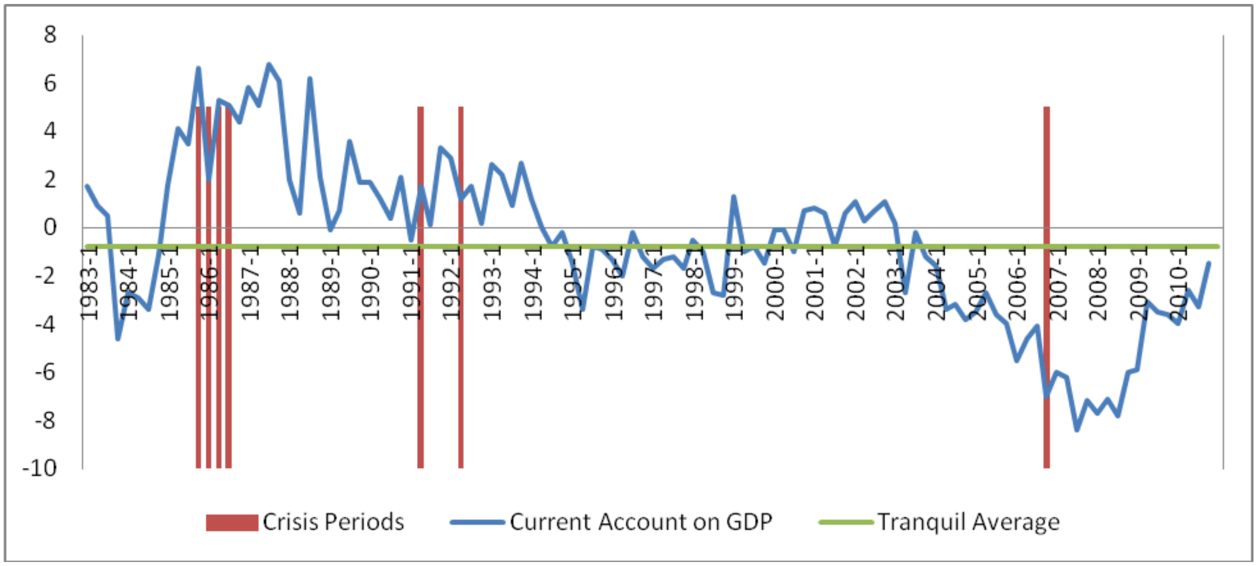
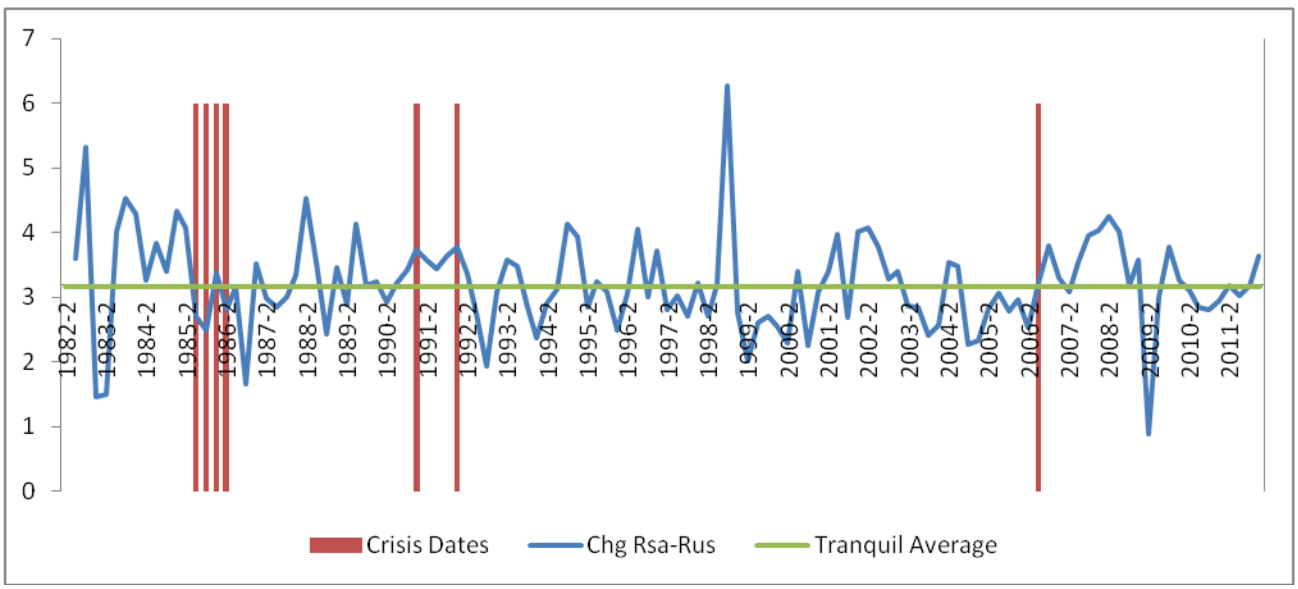
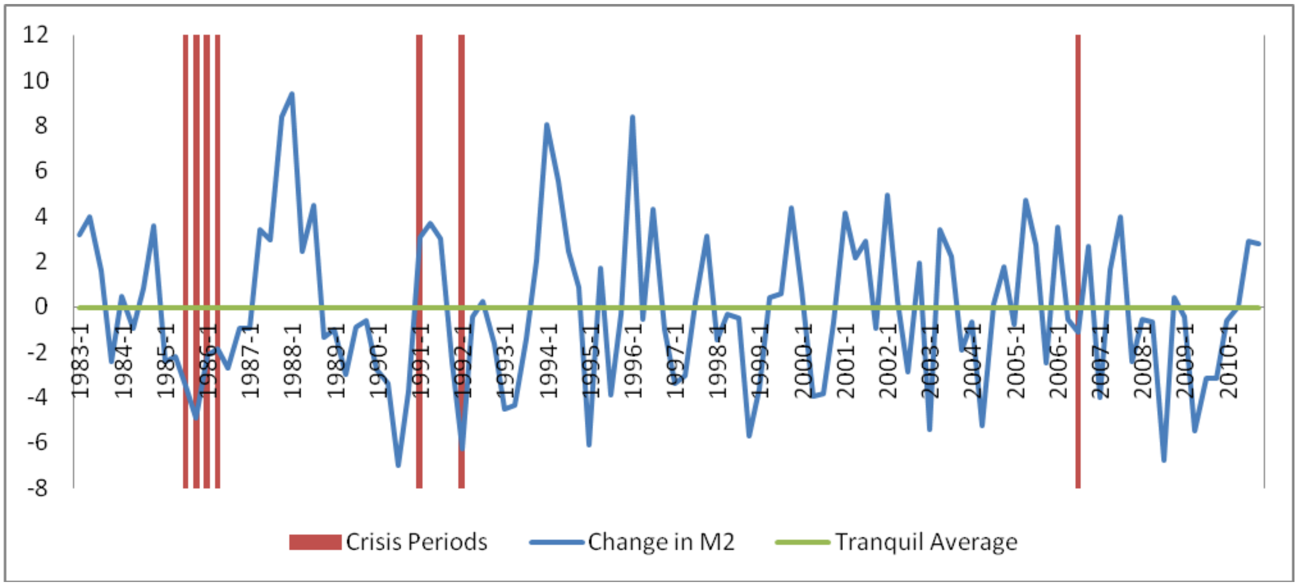
1985-1
1986-1
1987-1
1988-1
1989-1
1990-1
1991-1
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
Crisis Periods
Change in Investment on GDP
Tranquil Average

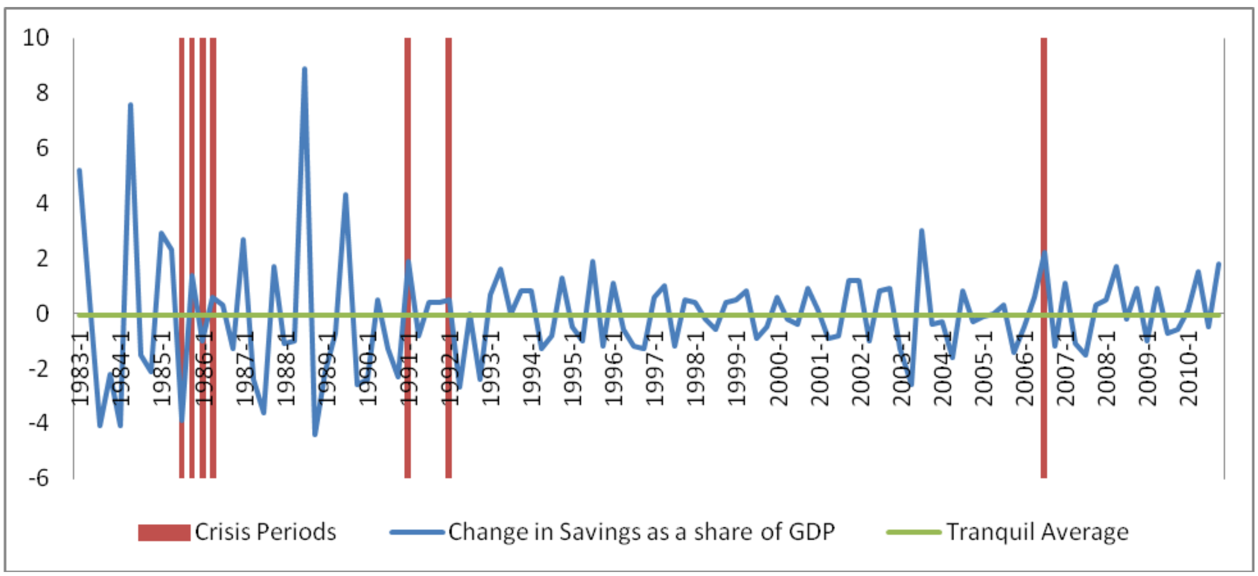


8
6
4
2
0
-2
-4
-6
-8
-10
1983-1
1984-1
1985-1
1986-1
1987-1
1988-1
1989-1
1990-1
1991-1
1992-1
1993-1
1994-1
1995-1
1996-1
1997-1
1998-1
1999-1
2000-1
2001-1
2002-1
2003-1
2004-1
2005-1
2006-1
2007-1
2008-1
2009-1
2010-1
Crisis Periods
Current Account on GDP
Tranquil Average



7
6
5
4
3
2
1
0
1982-2
1983-2
1984-2
1985-2
1986-2
1987-2
1988-2
1989-2
1990-2
1991-2
1992-2
1993-2
1994-2
1995-2
1996-2
1997-2
1998-2
1999-2
2000-2
2001-2
2002-2
2003-2
2004-2
2005-2
2006-2
2007-2
2008-2
2009-2
2010-2
2011-2
Crisis Dates
Chg Rsa-Rus
Tranquil Average


Crisis Periods
Change in M2
Tranquil Average


Crisis Periods
Change in Savings as a share of GDP
Tranquil Average

Variable	1985-Q3	1985-Q4	1986Q1	1986-Q2	1991-Q1	1992-Q1	2006-Q3
Change in Terms of Trade	Above Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean
Growth of Gold Prices	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean
Growth in Oil Prices	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean
Change in Real GDP	Above Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean
GDP/Capita	Above Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean
Growth of Foreign Reserves	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Approx. = Tranquil Mean	Above Tranquil Mean
Change in	Below	Below	Below	Below	Above	Above	Below

Investment/GDP	Tranquil Mean	Tranquil Mean	Tranquil Mean	Tranquil Mean	Tranquil Mean	Tranquil Mean	Tranquil Mean
Ratio of the Current Account to GDP	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean
Change in the Spread (Rsa-Rus)	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Approx. = Tranquil Mean
Change in M2	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Below Tranquil Mean
Change in Savings as a Share of GDP	Below Tranquil Mean	Above Tranquil Mean	Below Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean	Above Tranquil Mean

Table 7.1: The behavior of indicator variables during crisis periods in relation to their tranquil averages.

None of the variables shows the same behavior during all the crisis periods. That is, they may be higher than normal during one crisis and lower than their tranquil average during a different crisis. This makes it difficult to characterize the behavior of any of the chosen indicators during crisis periods. One can also use these graphics to look at behavior of variables before and after the crises take place. For example, the change in M2 falls below its tranquil mean before a crisis takes place. However, for the majority of the variables, it is difficult to characterize their pre- or post- crisis behavior as it is not consistent across all crisis periods.

However, a crisis that corresponds to an upper piercing of the boundary (an upper crisis) may stem from different factors than a crisis that corresponds to a lower boundary piercing (a lower crisis) and it is possible that indicator variables may behave differently under each of these scenarios. In fact, looking at table 7.1 it is clear that the change in real GDP, GDP/capita and the change in the spread exhibit different behavior during upper and lower crises; the change in real GDP and GDP/capita are below the tranquil mean during upper crises and above the tranquil mean during lower crises. The change in the spread is above the tranquil mean for upper crises and below the mean for lower crises.

8. Conclusion and Recommendations for Further Research

This paper reviewed the seminal literature on EWSs as well as discussed the relevant literature on debt crises. Following the literature review, the methodology behind creating EWS models was presented. Four EWS models are created to illustrate the methodology of creating Early Warning Systems. Three of the models are estimated using the OLS approach and the Logit approach. The fourth uses the Markov-switching approach outlined in Abiad (2003). A brief Graphical Analysis is also conducted.

This paper arrives at three useful models- model 1 in the logit context, model 2 in the logit context and model 3 in the OLS context. This finding is in line with that of Berg and Patillo (1999) and Edison (2003); that is, the models results are better than random guessing but are somewhat mixed. Having three EWS models that require some judgment in interpreting the results is not uncommon; the Bank of England uses a suite of models to forecast the crisis periods. The Markov-switching model predicted too many false positives and further development of this model is required. This task is left for future research.

Creating a functional EWS is no easy feat considering the variety of crises that can occur; this is especially true under circumstances of poor quality data. Given a finite set of indicator variables it is difficult to find models with a good predictive performance.

My immediate recommendation for future research would be to try to find other indicator variables that may lead to models with better forecasting performance than the ones presented in this paper. Also, the construction of the debt pressure variable used in this paper includes measures of both external and domestic debt for both the private and public sector. However, it is possible that different indicators may be more appropriate for public sector debt rather than private sector debt or visa-versa. Therefore, it may be interesting to construct two debt pressure variables, one for private sector debt and one for public sector debt and then forecast the crisis periods of each of these variables separately. This task is left for further researchers.

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Appendix

Indicator Variables used in other studies:

External	Monetary	Macroeconomic
export growth		public debt/GDP
terms of trade		inflation rate
current account/GDP		GDP per capita
growth of foreign exchange reserves		national saving growth
external debt/exports		real GDP growth rate
federal funds rate		
interest payments on external debt scaled to foreign reserves		
ratio of s/t to total external debt		
total private capital flows/GDP		
ratio of international reserves/total external debt		

Table A1: Variables used for Debt Crises. Source: Fedderke (2011)

Model 3 with the addition of GDPcon_5:

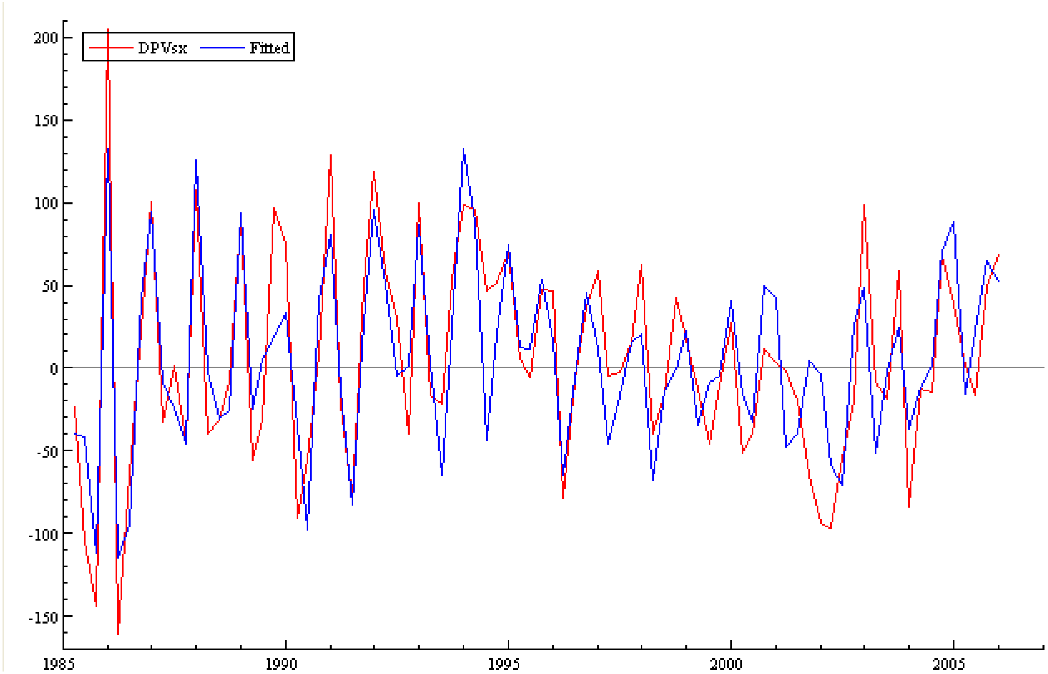
The estimation sample is: 1985(2) - 2006(1)

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
GDPcap_4	-0.571029	0.1060	-5.39	0.0000	0.3299
GDPcap_6	0.568386	0.1046	5.43	0.0000	0.3333
ChgSavGDP_8	-6.41831	2.668	-2.41	0.0193	0.0893
ChgTOT_8	5.20372	1.884	2.76	0.0076	0.1145
chg GDPcons_4	0.0155148	0.003209	4.83	0.0000	0.2837
chg GDPcons_7	-0.00443736	0.0008431	-5.26	0.0000	0.3195
chg GDPcons_8	-0.00461528	0.001669	-2.77	0.0076	0.1148
Chg Ln Gold_2	-140.306	79.69	-1.76	0.0835	0.0499
CAGDP_3	-2.18514	4.162	-0.525	0.6015	0.0047
PchgRES_4	-23.3512	19.97	-1.17	0.2469	0.0227
PchgRES_8	-37.3309	20.16	-1.85	0.0691	0.0549
Chg Rsa-Rus_6	-10.8322	5.663	-1.91	0.0606	0.0584
chgMtwo_7	-2.32567	1.625	-1.43	0.1576	0.0336
ChgSavGDP_3	-0.0547348	3.596	-0.0152	0.9879	0.0000
CAGDP_6	-5.14397	3.377	-1.52	0.1330	0.0378
CAGDP_2	-1.60707	3.311	-0.485	0.6292	0.0040
ChgTOT_6	-3.44969	1.911	-1.81	0.0762	0.0523
chgMtwo_6	2.56386	1.556	1.65	0.1047	0.0440
Chg Ln Oil_8	-46.8267	34.70	-1.35	0.1823	0.0299
Chg Ln Oil_4	-56.2543	37.76	-1.49	0.1416	0.0363
Chg Ln Oil_1	53.9229	36.12	1.49	0.1408	0.0364
CAGDP_4	2.50999	4.061	0.618	0.5389	0.0064
CAGDP_8	5.17722	2.822	1.83	0.0716	0.0540
Chg I/GDP_5	158.845	727.3	0.218	0.8279	0.0008
chg GDPcons_5	0.0161468	0.003379	4.78	0.0000	0.2790

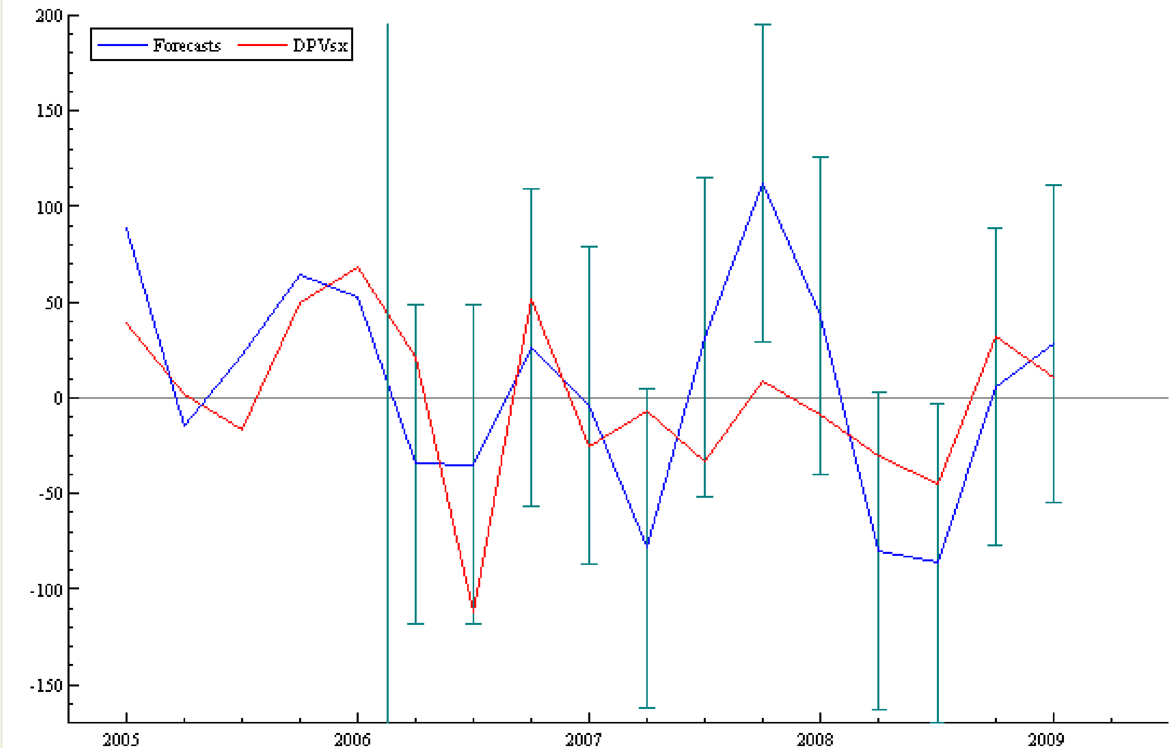
sigma	41.4927	RSS	101577.079
log-likelihood	-417.297		
no. of observations	84	no. of parameters	25
mean(DPVsx)	5.79204	se(DPVsx)	64.6985

In-sample performance:

The in-sample performance, in the case where, GDPcon_5 has been added to the model, is better than that of model 3; two additional crises have been picked up- 1985-Q4 and 1986-Q1. There are however, 2 false positives- 1988-Q1 and 1994-Q1.



Including the addition variable (GDPcon_5) has drastically worsened the out-of-sample forecast. The RMSE rises from 45.752 to 56.264 when the extra variable is added, thus the out-of-sample forecast worsens. The graph below illustrates that the 2006-Q3 crisis is not indicated but a false alarm is present in 2007-Q4.




```
Dynamic (ex ante) forecasts for DPVsx (SE based on error variance only)
     Horizon        Forecast         SE         Actual         Error    t-value
      2006-2        -34.7598      41.49        20.8714       55.6312      1.341
      2006-3        -34.7877      41.49       -112.788      -78.0001     -1.880
      2006-4         26.6042      41.49        51.7160       25.1118      0.605
      2007-1        -4.41913      41.49       -25.0673      -20.6482     -0.498
      2007-2        -78.5823      41.49       -7.11356       71.4687      1.722
      2007-3         31.4861      41.49       -32.8544      -64.3405     -1.551
      2007-4         111.858      41.49        8.62940      -103.228     -2.488
      2008-1         42.4136      41.49       -9.06736      -51.4810     -1.241
      2008-2        -79.7196      41.49       -30.1847       49.5349      1.194
      2008-3        -86.4302      41.49       -44.9787       41.4515      0.999
      2008-4         5.32092      41.49        32.1290       26.8081      0.646
      2009-1         28.0130      41.49        10.4960      -17.5171     -0.422
    mean(Error)  =       -5.4341     RMSE =       56.264
    SD(Error)    =        56.001     MAPE =       328.15
```

Markov-switching:

Bivarite Models from Section 6.4.1 (These regressions were run over the full sample)

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	7.91067	5.428	1.46	0.148
Constant(1)	-28.2176	48.24	-0.585	0.560
pGDPcap_1(0)	103.543	177.5	0.583	0.561
pGDPcap_1(1)	751.077			
sigma(0)	52.8382	3.828	13.8	0.000
sigma(1)	117.809	35.14	3.35	0.001
p_{0|1}	0.130978	0.1295	1.01	0.314

log-likelihood	-561.980277		
no. of observations	103	no. of parameters	
AIC.T	1137.96055	AIC	11.04816
mean(DPVsx)	5.35753	var(DPVsx)	3686.

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-8.98546	7.427	-1.21	0.229
Constant(1)	42.1843	8.061	5.23	0.000
PGDPcon(0)	-448.527	211.9	-2.12	0.037
PGDPcon(1)	-1092.71	185.5	-5.89	0.000
sigma(0)	53.5021	5.416	9.88	0.000
sigma(1)	46.4610	4.736	9.81	0.000
p_{0|0}	6.30350e-006	0.06606	0.00	1.000
p_{0|1}	0.978289	0.04618	21.2	0.000

log-likelihood	-551.856715		
no. of observations	103	no. of parameters	8
AIC.T	1119.71343	AIC	10.8710042
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	8.40554	5.419	1.55	0.124
Constant(1)	-32.1549	40.09	-0.802	0.424
P TOT_1(0)	-0.566501	1.920	-0.295	0.769
P TOT_1(1)	-14.4100	7.252	-1.99	0.050
sigma(0)	52.9394	3.812	13.9	0.000
sigma(1)	91.5597	26.89	3.41	0.001
p_{0|1}	0.141971	0.1356	1.05	0.298

log-likelihood	-560.505469		
no. of observations	103	no. of parameters	7
AIC.T	1135.01094	AIC	11.0195237
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-6.84219	3.436	-1.99	0.049
Constant(1)	9.16448	7.797	1.18	0.243
Chg Rsa-Rus_1(0)	-17.1911	2.576	-6.67	0.000
Chg Rsa-Rus_1(1)	7.85955	7.866	0.999	0.320
sigma(0)	10.2704	2.933	3.50	0.001
sigma(1)	67.4498	5.735	11.8	0.000
p_{0|0}	0.333382	0.1454	2.29	0.024
p_{0|1}	0.203646	0.07495	2.72	0.008

log-likelihood	-560.995801		
no. of observations	103	no. of parameters	8
AIC.T	1137.9916	AIC	11.0484622
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-23.0088	6.686	-3.44	0.001
Constant(1)	64.4559	6.128	10.5	0.000
CAGDP_1(0)	-5.18894	1.863	-2.78	0.006
CAGDP_1(1)	11.9478	1.712	6.98	0.000
sigma(0)	44.9244	4.407	10.2	0.000
sigma(1)	26.0656	4.205	6.20	0.000
p_{0|0}	0.693042	0.07631	9.08	0.000
p_{0|1}	0.620239	0.1335	4.65	0.000

log-likelihood	-554.096309		
no. of observations	103	no. of parameters	8
AIC.T	1124.19262	AIC	10.9144914
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-72.0389	23.72	-3.04	0.003
Constant(1)	11.0108	6.932	1.59	0.116
PchgRES_1(0)	-86.2700	63.85	-1.35	0.180
PchgRES_1(1)	-2.63714	24.34	-0.108	0.914
sigma(0)	33.5873	18.87	1.78	0.078
sigma(1)	57.8875	4.882	11.9	0.000
p_{0|0}	0.686652	0.2039	3.37	0.001
p_{0|1}	0.0144319	0.02010	0.718	0.475

log-likelihood	-566.852614		
no. of observations	103	no. of parameters	8
AIC.T	1149.70523	AIC	11.1621867
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-48.5774	49.28	-0.986	0.327
Constant(1)	8.20852	5.404	1.52	0.132
ChgSavGDP_1(0)	22.8504	20.55	1.11	0.269
ChgSavGDP_1(1)	-0.958679	3.244	-0.296	0.768
sigma(0)	112.042	32.55	3.44	0.001
sigma(1)	52.9632	3.817	13.9	0.000
p_{0|0}	0.859445	0.1338	6.42	0.000

log-likelihood	-561.720318		
no. of observations	103	no. of parameters	[illegible]
AIC.T	1137.44064	AIC	11.04311
mean(DPVsx)	5.35753	var(DPVsx)	3686.2

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-23.4714	21.36	-1.10	0.275
Constant(1)	9.41590	17.26	0.545	0.587
Pm2_1(0)	-200.065	401.2	-0.499	0.619
Pm2_1(1)	734.231	347.7	2.11	0.037
sigma(0)	48.8212	8.057	6.06	0.000
sigma(1)	49.2574	8.797	5.60	0.000
p_{0|0}	0.514829	0.1976	2.61	0.011
p_{0|1}	0.403852	0.2324	1.74	0.086

```
log-likelihood    -566.729676
no. of observations       103  no. of parameters            8
AIC.T              1149.45935  AIC                 11.1597995
mean(DPVsx)           5.35753  var(DPVsx)             3686.21

Linearity LR-test Chi^2(5)  =   2.8130 [0.7288]   approximate upperbound: [0.9342]

Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)
```

	Regime 0,t	Regime 1,t
Regime 0,t+1	0.51483	0.40385
Regime 1,t+1	0.48517	0.59615

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	2.03464	5.715	0.356	0.723
Constant(1)	123.332	3.910	31.5	0.000
Chg I/GDP_1(0)	858.190			
Chg I/GDP_1(1)	-15625.6	1102.	-14.2	0.000
sigma(0)	56.0919	4.031	13.9	0.000
sigma(1)	2.83848	1.269	2.24	0.028
p_{0|0}	0.970379	0.02052	47.3	0.000

```
log-likelihood     -563.03483
no. of observations       103  no. of parameters            7
AIC.T              1140.06966  AIC                 11.0686375
mean(DPVsx)           5.35753  var(DPVsx)             3686.21
```

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	8.81936	5.532	1.59	0.114
Constant(1)	-22.1135	38.02	-0.582	0.562
Chg Ln Oil_1(0)	-20.6347	36.12	-0.571	0.569
Chg Ln Oil_1(1)	268.761	134.8	1.99	0.049
sigma(0)	52.6961	3.919	13.4	0.000
sigma(1)	90.6707	24.81	3.65	0.000
p_{0|1}	0.113127	0.1296	0.873	0.385

log-likelihood	-560.406518		
no. of observations	103	no. of parameters	7
AIC.T	1134.81304	AIC	11.0176023
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

The estimation sample is: 1985(2) - 2010(4)

	Coefficient	Std.Error	t-value	t-prob
Constant(0)	-3.03012	7.033	-0.431	0.668
Constant(1)	69.2025	19.17	3.61	0.000
Chg Ln Gold_1(0)	-35.4799	74.08	-0.479	0.633
Chg Ln Gold_1(1)	534.986	112.7	4.75	0.000
sigma(0)	54.0990	4.567	11.8	0.000
sigma(1)	19.3715	8.185	2.37	0.020
p_{0|0}	0.884943	0.07172	12.3	0.000
p_{0|1}	0.959534	0.1757	5.46	0.000

log-likelihood	-563.630212		
no. of observations	103	no. of parameters	8
AIC.T	1143.26042	AIC	11.0996158
mean(DPVsx)	5.35753	var(DPVsx)	3686.21

Multivariate Markov-Switching model, full sample:

```
              The estimation sample is: 1985(2) - 2010(4)

                  Coefficient  Std.Error  t-value  t-prob
Constant(0)          -23.1959      7.209    -3.22   0.002
Constant(1)           67.2056      7.641     8.80   0.000
CAGDP_1(0)           -4.90263      2.006    -2.44   0.016
CAGDP_1(1)            11.6118      1.915     6.06   0.000
PGDPcon_1(0)          70.8099      153.0    0.463   0.645
PGDPcon_1(1)         -216.560      283.8   -0.763   0.447
sigma(0)              45.1185      4.577     9.86   0.000
sigma(1)              26.2480      4.510     5.82   0.000
p_{0|0}              0.680696    0.07945     8.57   0.000
p_{0|1}              0.640147     0.1513     4.23   0.000

log-likelihood    -553.869611
no. of observations       103  no. of parameters          10
AIC.T              1127.73922  AIC                10.9489245
mean(DPVsx)           5.35753  var(DPVsx)            3686.21

Linearity LR-test Chi^2(6)  =   30.060 [0.0000]** approximate upperbound: [0.0000]**
```

```
Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)
                Regime 0,t   Regime 1,t
Regime 0,t+1       0.68070      0.64008
Regime 1,t+1       0.31930      0.35992
```

Baseline Markov-switching model with constant transition probabilities:

```
Switching( 4) Modelling DPVsx by MS(2)
              The dataset is: C:\Documents and Settings\Administrator\Desktop\Thesis Nov\OXDATA3.xls
              The estimation sample is: 1985(2) - 2010(4)

                  Coefficient  Std.Error  t-value  t-prob
Constant(0)           8.22709      5.409     1.52   0.131
Constant(1)          -37.7093      50.98   -0.740   0.461
sigma(0)              52.9598      3.830     13.8   0.000
sigma(1)              122.217      36.18     3.38   0.001
p_{0|1}              0.134506     0.1310     1.03   0.307

log-likelihood    -562.350515
no. of observations       103  no. of parameters           5
AIC.T              1134.70103  AIC                11.0165149
mean(DPVsx)           5.35753  var(DPVsx)            3686.21

Linearity LR-test Chi^2(3)  =   13.473 [0.0037]** approximate upperbound: [0.0037]**

Transition probabilities p_{i|j} = P(Regime i at t+1 | Regime j at t)
                Regime 0,t   Regime 1,t
Regime 0,t+1        1.0000      0.13451
Regime 1,t+1       0.00000      0.86549
```