Graduate Institute of
International Studies | Geneva
Economics

HEI Working Paper No: 14/2007

# Parametric and Non-Parametric Approaches to Exits from Fixed Exchange Rate Regimes

Ahmet Atil Asici
Graduate Institute of International Studies

## Abstract

Following the demise of the Bretton-Woods increasing number of countries has been opting for flexible exchange rate regimes. Exiting from fixed regimes however is not without costs. Regime transitions have often been occurred in the midst of a crisis which has considerable economic costs. Given the big number of countries having still fixed regimes and financial markets that are fairly close and expected to be liberalized sooner or later, issue of exiting a peg without incurring crisis is a real challenge confronting these countries. The aim of this paper is to determine the conditions under which orderly exit is possible. The paper employs Binary Recursive Tree and standard regression frameworks. Analysis shows that countries with higher output gap and overvalued real exchange rate, among others, are doomed to exit in a disorderly way. The ill-managed financial liberalization and macroeconomic stabilization programs seem to lay the seeds of instability. An interesting finding is that the conventional strengths of parametric regression analysis can be dramatically improved by utilizing findings of non-parametric BRT technology. Sample contains all countries depending on the data availability, and covers 1975-2004 period.

# Parametric and Non-Parametric Approaches to Exits from Fixed Exchange Rate Regimes

**Ahmet Atıl Aşıcı**[1]

Graduate Institute of International Studies

July 2007

[1] I would like to thank to Charles Wyplosz, Richard Baldwin, Philippe Bacchetta and Alexander Swoboda for their useful comments and suggestions. Material support of Economics department of HEI is greatly acknowledged.

# I. Introduction and Literature Review

Following the demise of Bretton-Woods, trade and financial globalization has taken a fresh start. Intensifying linkages among countries reqiure them to align their economic policies, including exchange rate regime policies, with the new rules brought by the new economic order. In this new era, the attractiveness of fixed regimes (hard or soft) has been on a continuous decline. This is especially true after the dramatic experiences of emerging market countries in the 1990s and early 2000s. The transitions have not, however, been painless. Many countries experienced harsh economic conditions during the move from pegged to flexible regimes. When and how to exit is an extremely important issue given the nature of the economic consequences involved. And this constitutes the main aim of this paper, namely to determine the conditions behind orderly exits.

The issue of exiting from fixed to flexible regimes lies at the junction of two rich bodies of literature: currency crisis and regime choice. The currency crisis literature falls short in accounting for orderly regime transitions. The regime choice literature, on the other hand, does not consider the consequences of this choice. It is within this niche that this study sits.

The empirical literature on exiting was initiated by a study by Eichengreen and Masson (1998). Relying on case study analysis, the authors find that most countries hesitate to leave a peg when things are going "well" and consider the option of exit only when forced to do so, in other words, when it is too late. Building on this study, Asici (2002) and Asici and Wyplosz (2003) employ probit models to determine the conditions behind orderly exits. Their findings are in line with a recent theoretical study by Rebelo and Vegh (2006) which asserts that exits are more likely to be orderly when undertaken in favorable conditions (sound macroeconomics, adequate banking systems and a period of capital inflows). In Asici et al. (2007), an inherent sample selection bias problem is dealt with by employing Heckman Selection Models proposed by Heckman (1979). Interestingly, this study finds that the macroeconomic discipline represented by budget and current account balance does not seem to be important in determining the type of exit. The role of capital controls is found to be important: while these make exits less likely, once a country exits, they increase the likelihood that this will be orderly, a conclusion which contradicts the common wisdom.

Other closely related empirical papers can be listed as follows.

Klein and Marion (1997) examine the determinants of de-pegging, which include both realignments within an exchange rate regime and exits to a more flexible regime. They do not distinguish among these two categories, however, nor are they interested in the conditions under which de-pegging is orderly or not. Duttagupta and Otker-Robe (2003) extend the Klein and Marion study by analyzing the conditions that lead to orderly exits. They use a multinomial logit procedure to allow for five different outcomes: realignments within the same regime, orderly exits to more or to less flexible regimes, and "exchange rate pressure episodes", which may occur within the same exchange rate regime or not.

Masson and Ruge-Murcia (2005) focuses entirely on exits by estimating time-varying transition probabilities among three exchange rate regimes (fixed, intermediate, flexible). The authors then try to explain the estimated probabilities with macroeconomic factors. Agénor (2004) provides a detailed study of three exit episodes, with special emphasis on capital flows. In his study, exits encompass moves from intermediate regime types to the two extremes of hard pegs or free floats. Detragiache et al. (2005) use multinomial logits to estimate the difference between orderly and disorderly exits, using no exits as the reference situation.

In a recent paper, Aizenman and Glick (2006) study the empirical and theoretical association between the duration of a pegged regime and the cost incurred upon exiting the regime, where the exchange rate is used as a commitment device. They find that hard pegs, especially arrangements like currency boards, increase the credibility of authorities in tackling inflation by raising the cost of devaluation and regime change. In turn, however, the duration of pegs tends to increase as fragilities build up. Increasing credibility through pegging thus comes at a cost, namely the pain following exit.

This paper is a generalization of Asici et al. (2007). Apart from the use of an expanded dataset, the paper makes two additional contributions to the existing literature. Firstly, it introduces a new non-parametric technique, known as Classification and Regression Tree (CART thereafter) analysis to study the issue, alongside standard regression techniques. Secondly, it proposes a way to merge these two approaches.

As a nonparametric technique CART has some superior features over standard methods especially in areas where the relationships amongst variables tend to be nonlinear rather than linear, such as, crises. Manasse et al. (2003) use CART to accompany their logit model in predicting sovereign debt crises. Similarly Ghosh and Ghosh (2003) analyze the role of structural vulnerabilities in currency crises with the help of a classification tree. Kaminsky (2003), on the other hand, emphasizes that currency crises can take various types and pins down the different paths leading to different types of currency crises.

CART allows working with both categorical and continuous dependent variables. When the dependent variable is categorical (binary or multi-level) the tree is called as *classification tree* and when it is continuous the tree is called as *regression tree*. In classification tree analysis the main idea is to find a set of **general** (applicable not only to an individual observation but to as many observations as possible) rules so as to maintain the different types of observations (i.e. crisis, tranquil) in separate parts of the tree as **homogenous** (crisis and tranquil observations in separate nodes) as possible. While preserving the main idea, in regression tree analysis, the algorithm tries to find a set of **general** rules so as to maintain similar observations (with respect to dependent variable) in separate parts of the tree as **close** (close to mean or median value within the node) as possible.

The classification and regression tree algorithms will be explained in detail further in the text but before that let us have a quick look at the problem of classification tree analysis with the help of a simple, hypothetical example. Assume that we have 50 observations, 20 Class-A type (i.e. debt default) and 30 Class-B (i.e. tranquil). For these observations, assume further that, we have only two variables (i.e. short-term debt to GDP and inflation rate) to explain the occurrence of debt defaults. Figure 1 illustrates the distribution of these observations on the X-Y plane.

A classification solution that characterizes the Class-type as a function of variables X and Y can be useful in understanding how these variables affect the occurrence of debt defaults.

**Figure 1The Distribution of Class-A and Class-B Observations**

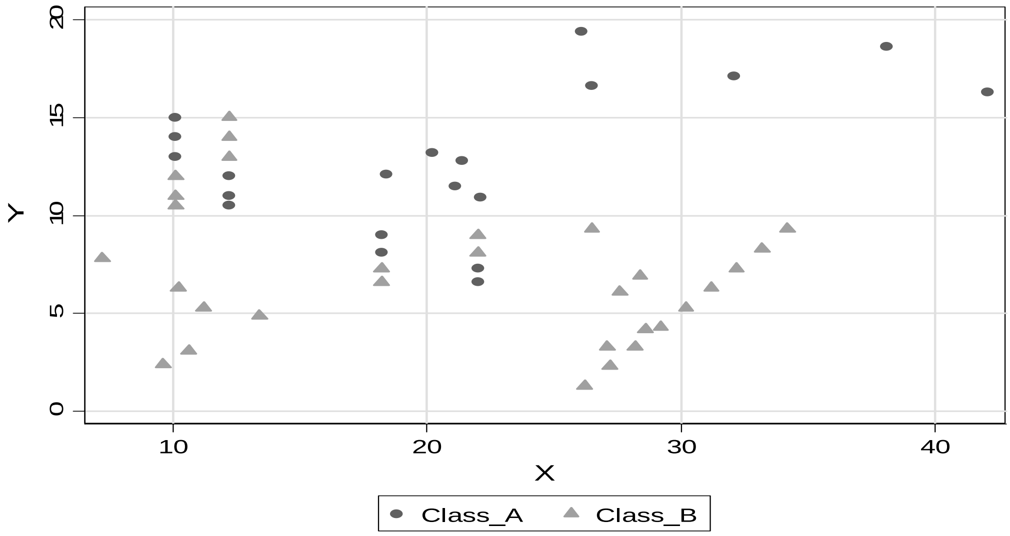
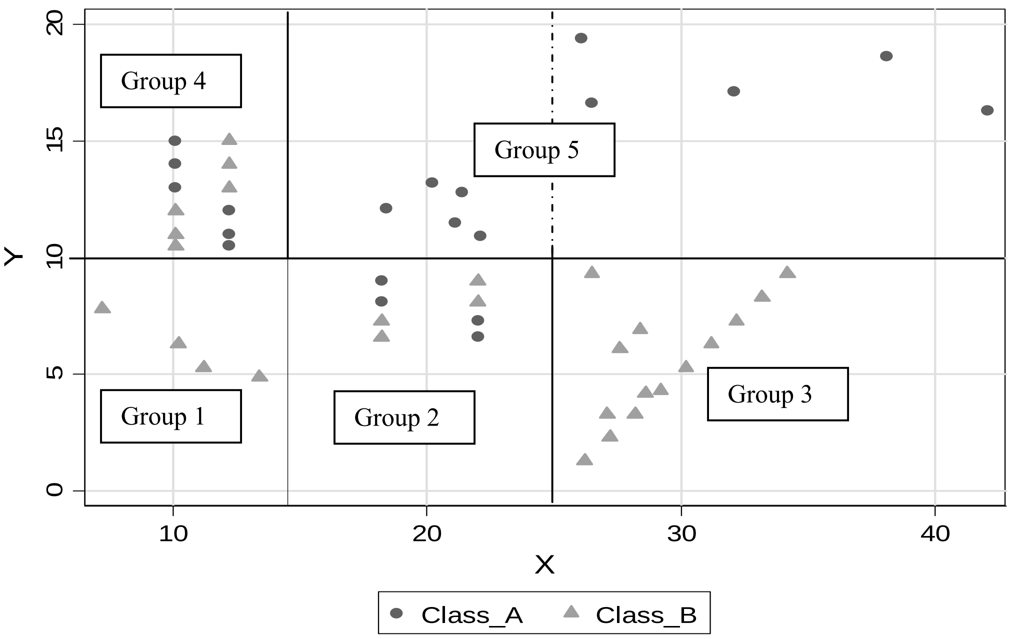


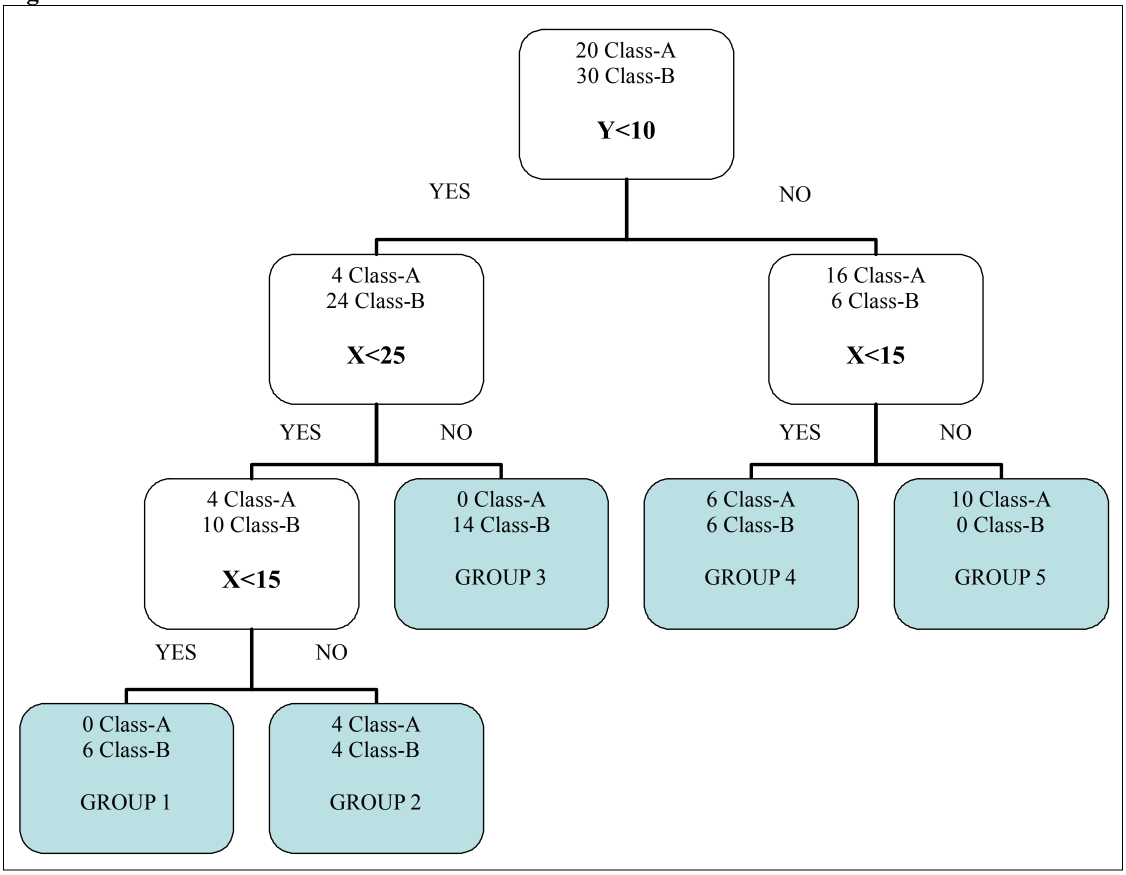

Figure 2 shows two vertical (x=15 and x=25) and one horizontal axis (y=10), that seem to partition the two class-types into 5 different groups quite successfully.

**Figure 2The Partitioning into Groups**




The obvious questions like where to start partitioning, i.e. by using which variable and at what value, become increasingly difficult as the number of variables and observations increases. Classification tree analysis provides automated techniques for exploring these kinds of axis parallel partitions. Figure 3 illustrates a classification tree that corresponds to the partitions shown in Figure 2.

**Figure 3The Classification Tree**




Starting from the top node, algorithm starts to test all possible partitions. Since we have 50 observations and two explanatory variables the number of candidate splits to be tested is 100. By eye-checking it is easy to see that at the beginning best partition (hence the most powerful among others) can be made by drawing a line at y=10. As a result, we can almost completely separate Class-B observations from Class-A. Observations satisfying Y<10 rule splits off to left and those not to right. For the observations on the left node where we have 4 Class-A and 24 Class-B observations, it is still possible to find a rule to partition observations further. Note that when Y<10 and X>=25, we do not have any Class-A observations left in the right node, hence X<25 can be a perfect rule. These observations, hence, form Group 3.

The algorithm recursively searches for splits to get the groups as pure as possible. With 4 splits (X<15 conditional on X<25 and Y<10, X<25 conditional on Y<10, X<15 conditional on Y<10 and Y<10) we managed to isolate perfectly the observations within Group 1, Group 3 and Group 5. It is theoretically possible to further split Group 2 and Group 4 observations by assigning some further rules, but these splits do not add any information. Note that the class ratio within these nodes is 1-1, same number of observation from each class. Partitioning can only make sense if it would have led to a change in class ratios. Unfortunately, it is not possible to increase the purity of Group 2 and Group 4 observations by partitioning, since there exists no vertical or horizontal line that can isolate one class better than current partition. In other words, change in improvement by partitioning is zero for all possible splits and it is where the tree growing stops.

Next step is to assign the class of the nodes, i.e. default prone or tranquil. It is decided over the relative frequencies of classes within each node. Note that Class-A (Class-B) observations constitute 40% (60%) of the sample. Hence, the unconditional probability of, say debt default, is 40%. Taking this value as a benchmark, the group with a higher (lower) concentration of Class-A observations is assigned as a default prone (tranquil) node. As a result, Group 2, 4 and 5, where the conditional probability of observing Class-A observation is higher than 40%, are called as default prone nodes and Group 1 and 3 as tranquil.

Classification (and regression) tree algorithms can be evaluated by their accuracy, speed and interpretability. Predictive accuracy on unseen data constitutes the main reference point in comparing the solutions of different approaches. The inherent noise in real-world data may affect the solution and decrease the predictive accuracy of the tree grown. The most common way to deal with this problem is by dividing the sample into two parts. The first part is used to grow the tree and the second part is used to test the accuracy of the rules found. If the rule is found to be inapplicable to the observations in the testing subsample, it will be dismissed from the tree, leading to a smaller tree than presented in Figure 3. As seen, there is a trade-off between the purity and the applicability of the tree. As the tree size shrinks, rules become more general and applicable, but it comes at the expense of decreasing purity of the groups. Comparison made over the misclassification rates of different subtrees can strike a fair balance between purity and applicability. The subtree which fares better in placing the testing observations within right groups is chosen as an optimal tree. It will possibly be smaller in size than the maximal tree but its predictive accuracy when tested with new data will be higher, and hence more robust.

The plan of the paper is as follows. Section II describes the dataset and the sample. The methodology is explained in Section III. Then, in Section IV, we present two models, called as EXIT and DGAPT models, a classification and a regression tree analysis, respectively, and discuss results. A set of robustness checks is presented in this section. Results of parametric analysis and comparison of the two approaches can be found in Section V. Section VI concludes.

## II. Data and Sample

### II.1 Exit Definition

In this study, we use the regime classification proposed by Reinhart & Rogoff (R&R) (2004) to determine exit (and no-exit) dates. As is now well documented, “fear of floating” and “fear of fixing” prevent countries from announcing their “true” regime, and studies show that officially announced *de jure* regimes often do not match the *de facto* regimes observed (see Genberg and Swoboda, 2005). R&R, therefore, use market-determined/blackmarket exchange rates to classify regimes, on the grounds that underlying monetary stance of authorities can best be represented by these rates and not by their official announcements.

R&R define 13 exchange regime categories, ranging from the absence of a domestic currency (dollarization) to a pure free float. The authors also define an additional category – freely falling –

corresponding to high inflation and continuing depreciation, within which they rank countries along the previous 13 categories.

Following the logic of Asici et al. (2007), we define a regime as fixed if there is a commitment (implicit or official) by the authorities to the regime. The rationale is that any such commitment stands to be challenged so long as authorities stand ready to honor these commitments. It does not matter whether the band is wide or narrow, horizontal or moving. Accordingly, regimes 1-11 in the R&R denomination are reduced to a single category which we call fixed, while categories 12-13 in the R&R scheme are considered as flexible regimes. Exits are, then, defined as transitions from regimes 1-11 to 12-13.

We employ a 3-year exclusion window for exit and non-exit cases. To fall into the exit sample, a regime must exhibit at least 2 years of pegging followed by at least 1 year of floating. This is designed to eliminate cases of rapid re-pegging, possibly followed by rapid exit, which we consider as one exit event. The longer pre-exit period is chosen to ensure that we only deal with cases where the peg has been in place for a substantial period before exit. No-exit cases are arbitrary in the sense that nothing happens. The chosen procedure is to apply the same three-year exclusion window as that used for exit cases.

In this vein, for each country, we adopt the following procedure:

- If the country never exits during the sample period, we partition the period in as many three year sub-periods as possible, leaving out what remains at the end. Each of these three-year sub-periods is treated as the no-exit analog of the exit cases, i.e. t = 0 corresponds to the observation two years after the beginning of the sub-period.

- If the country exited once, we start from the exit case and its associated three-year window. From there, we move to the left and to the right and identify as many three-year windows as possible.

- If there are several exit cases, we proceed as above, filling up the periods in-between exits and both ends with as many three-year windows as possible. Since there are many ways of filling the periods in-between exits, we arbitrarily move leftwards.

There exist different criteria to distinguish orderly exits from disorderly ones. In this study, as in Asici et al. (2007), the exit type is determined on the basis of the evolution of the output gap. Exit is classified as orderly if the change in output gap between t+1 and t-1 is greater than -3, disorderly otherwise, t being year of exit.[2]

$$y_{i,t} = output\_gap_{i,t+1} - output\_gap_{i,t-1}$$

The output gap is computed by detrending real GDP using the Hodrick-Prescott filter and measured as the percentage deviation of real GDP from its trend.

### II.2 Sample

The sample is assembled from the R&R country chronology dataset which goes until end 2001. A recent study by Eichengreen and Razo-Garcia (2006) expands this dataset to the end of 2004. Since one of the aims of this study is to compare the results obtained with those found in standard regression framework, we will use the same sample as in Asici et al. (2007). This sample contains 566 cases, 59 exits and 507 no-

---

[2] Moderate depreciation around exit time (between t-6 and t+6, t being exit month), less than 25% more specifically, can also be taken as a criterion to define orderly exits.

exits after applying the 3-year window and omitting currency union cases[3], and covers the period from 1975 to 2001. An expanded sample contains 650 observations, 68 exits and 582 no-exits, covering the period from 1975 to 2004. This expanded sample will be used for robustness checks. Exit and no-exit observations with dates can be found in Appendix 3., where the original sample observations are highlighted in bold.

**II.3 Explanatory Variables**

The issue of exiting from fixed to flexible regimes lies at the junction of two rich bodies of literature: regime choice and currency crisis. Levy-Yeyati et al. (2006) analyze the determinants of regime choice by testing three hypotheses: *Optimum Currency Area* (OCA), *financial integration,* and thirdly, *political crutch*. Countries may opt to have greater exchange rate flexibility in order to cope with changing economic conditions. From that perspective, exits can be seen as voluntary decisions. OCA theory relates regime choice to economic structure. It predicts that a pegged regime is more desirable the higher is the degree of trade integration, but harder to sustain when an economy is subject to large real shocks, i.e. terms of trade shock in the absence of price/wage flexibility and labor mobility. The financial integration view highlights the consequences of financial integration for regime choice. According to this hypothesis, as financial integration increases, a higher occurrence of flexible regimes is likely to occur. In the third framework, that of political crutch, theory suggests that fixed regimes are more likely if the country lacks a good institutional track record, but more likely if the government is too weak to sustain them (ibid. p:5).

Exit decisions may, however, be made involuntarily. Speculative attacks may force governments to adopt more flexible regimes. The currency crisis literature, with its several generations of crisis models, investigates the different sources of vulnerabilities. In first generation models, the source of vulnerability is the inconsistency between the exchange rate regime and macroeconomic policies. Symptoms of this inconsistency can be found in real exchange rate overvaluation and current account deficit. Second generation models emphasize domestic economic and political vulnerabilities that may prevent authorities from upholding a fixed regime notably when faced with a speculative attack. Unemployment, negative output gaps are considered to be important indicators of an impending speculative attack in these models. Third generation models, on the other hand, highlight financial maturity and currency mismatches as key sources of vulnerability. The relevant indicators in these models include external debt, banking sector liquidity, and financial depth variables.

Speculative attacks on fixed regimes lie at the heart of voluntary exits as well as involuntary ones. A speculative pressure index is often used in the literature to pin down the exact date of these attacks and crises. However, these indices can also be used to detect mounting pressure. A small interest rate increase to combat a short-lived speculative attack can be detrimental in the medium-term for its adverse effect on debt dynamics, even if it may be undetected when using the standard index. One can extract this information by slightly altering the computation of the standard speculative pressure index, which is calculated based on a weighted average of monthly changes in the exchange rate, interest rate and in

[3] Exiting from a currency union is more of political than economical in nature, see Edwards and Magendzo (2003) for a discussion.

international reserves. The standard index takes a value of 1 if the pressure exceeds a specific threshold (mean plus 3 standard deviations is commonly used as the threshold). We intend to use this measure not only as a *bell* marking the beginning date of crisis but also as a sort of *early-warning device*. This can be done by, first lowering the threshold and extending the monitoring period of the measure. The binary indicator, *forced,* is computed by using a mean plus one standard deviation threshold and takes a value of 1 when the pressure measure exceeds this threshold in any of the 12 months preceding exit. The computational details are explained in Appendix.

## III. Methodology

The methodology followed in this paper consists of parametric and non-parametric forms. In the first part, we employ a non-parametric CART methodology. We present and discuss two models, classification and regression trees, called EXIT and DGAPT models which carry the names of the dependent variables used. In the parametric part we employ probit and Heckman selection models. Note that the parametric part is not meant to provide a full account of exiting (see Asici et al. (2007) for a full-fledged parametric analysis) but rather to show how non-parametric CART analysis changes and improves the results obtained from parametric methods. Before discussing the conditions leading to exit and no-exit, let us first outline the CART procedure.

### III.1 CART Procedure

In this part I would like to explain the algorithms used to grow classification and regression trees. Both algorithms share many common elements, tree growing, testing, optimal tree selection etc. But the nature of the dependent variable forces a modification in some parts of the algorithm, like splitting criterion selection, the calculation of misclassification rate etc. I will start by explaining classification tree algorithm and indicate modifications in the case of regression tree where it is needed.

CART procedure consists of three steps:

i. Setting options
ii. Maximal tree growing and class assignment and
iii. Testing and optimal tree selection.

Now let us see these steps in detail.

**i. Setting Options**

The researcher intervenes in setting the options. Selected options are then used by the algorithm in maximal tree growing and optimal tree selection steps. Clearly, with different set of options one can build slightly different trees. The options and their possible effects on the tree are discussed below. As will be seen, the sensitivity of trees to changes in some options is quite high. Again, for some options the choice may be quite obvious, like splitting criterion selection which depends mostly on the nature of the dependent variable. But in the case of maximum child node size option, the selection of particular size is not evident. Therefore it is quite an important issue to justify the selection of a particular option.

**a) Splitting Criterion:**

CART grows trees by splitting observations. Depending on the structure of the dependent variable (categorical or continuous, binary or multi-level etc.) an appropriate choice of splitting criterion is indispensable. CART splits a node into two child nodes depending on the answer given to the question posed in the parent node. Questions are formulated so as to generate “yes” or “no” answers. For example, whether inflation is lower than 10 percent or not. “Inflation lower than 10” is a rule known as splitter in CART jargon. Observations satisfying this condition go to left child nodes, while others split off to the right. CART compares all splitters by computing the improvement (see below for exact formula) they make. The splitter which yields the maximum increase in purity within the left and right child nodes is chosen as a *primary splitter*. Different splitting criteria employ different formulas in calculating improvement scores. The default criterion for classification trees is called GINI which puts the priority on obtaining the most populous class of observation in right nodes. ENTROPY (see below), one of the alternative criteria, on the other hand, puts the emphasis on obtaining a rare class of observations. If the dependent variable consists of more than 2 classes of observations, TWOING is recommended. In the case of a continuous dependent variable, in regression tree analysis in other words, two splitting criteria are available, LEAST SQUARE and LEAST ABSOLUTE DEVIATION (see below).

Given its relative importance in the algorithm, the splitter selection criterion option is explained in detail below.

**1. A Closer Look at Entropy Splitting Criterion**

Because of its emphasis on the correct classification of rare class observations (exits in our case), we choose to employ **Entropy** splitting criterion in growing our EXIT model classification tree. Note that we have two classes of observations, exit and no-exit, with former representing 10.4% of the sample.

Now let us have a look at *how entropy splits nodes*.

In node $t$ we have $m$ different classes (exit, no-exits etc.) with proportions represented by $p\ (j \mid t)$, where $j = 1,2,...,m$. Thus, within node $t$ we have $\Sigma\, p\ (j \mid t) = 1$.

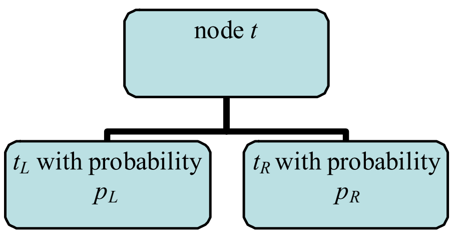
We define a measure $i(t)$, impurity of $t$, as a nonnegative function of the $p(\, j \mid t)$ such that

$$i(t) = -\sum_{j=1}^{m} p(j \mid t) * \ln p(j \mid t)$$

Then, CART tries all splitters to split observations in node $t$ into left and right child nodes and computes the **goodness of the split**. This is defined as the **decrease in impurity (improvement)** and takes the form

$$\boldsymbol{\Delta i(t)=i(t)-p_L i(t_L)-p_R i(t_R)}$$

where $p_L$ and $p_R$ represent probabilities of class $j$ being in left and right child nodes, and where $i(t_L)$ and $i(t_R)$ represent the impurity of left and right child nodes, respectively.



**After comparing the improvement scores of all splits in the candidate set**, which is defined as S, CART chooses **that split which generates the highest degree of improvement (largest decrease in impurity).**

$$\Delta i(s^*,t) = \max_{s \in S} \Delta i(s,t)$$

The process above continues, with cases split further within left and right child nodes. Splitting is **stopped at node *t*** when the change in impurity ($\Delta i$) after splitting it into left and right child nodes is **0.**

**2. A Closer Look at Least Absolute Deviation Splitting Criterion**

CART enables us to work with continuous dependent variables as well. In this case, the tree is called a Regression Tree. Splitter selection follows a similar logic but since it is not appropriate to talk about different classes of observations, since there is now a continuum of observations, CART uses different criteria, namely *Least Squares* and *Least Absolute Deviation (LAD).* In growing regression trees we use LAD as a splitting criterion and the splitter selection is made as follows.

Under the LAD criterion, **node impurity** is measured by the **within-node sum of absolute deviation**, *AD(t)*, which is defined as

$$AD(t) = \sum_{i=1}^{N_t} \left| y_{it} - \overset{\approx}{y}_t \right| \quad \text{for i=1, 2, ...., } N_t$$

where $y_{it}$ is the individual value of the dependent variable and $\overset{\approx}{y}_t$ is the median of the dependent variable at node *t*. $N_t$ is the number of observations in node *t*.

Given the impurity function, $AD(t)$ and the splitter *s* that sends cases to left $(t_L)$ and right $(t_R)$ child nodes, the **goodness of a split** is measured by the function

$$\Delta i(t) = AD(t) - AD(t_L) - AD(t_R)$$

where $AD(t_L)$ and $AD(t_R)$ are the sums of the absolute deviation in left and right child nodes. Within the candidate set S, **the splitter generating the maximum improvement** (by minimizing the absolute deviation of the dependent variable within the node), *s*,* is chosen as a **primary splitter**.

$$\Delta i(s^*,t) = \max_{s \in S} \Delta i(s,t)$$

Again this process continues until no further improvement is possible. At the end of this process, we reach the maximal tree. Note that this tree is not optimal, since nothing has been done to check its robustness. This will be done in the testing phase as will be mentioned below.

**b) Node Size:**

Researchers can set the minimum (maximum) size of child (parent) nodes. Depending on the subject of interest it may not make sense to have child or terminal nodes containing only one observation. Equally, the researcher may not want the node to split further after reaching a certain size. The default minimum size for a child node is one and the maximum size for a parent node is ten. One can increase the child node and decrease the parent node size by changing the corresponding parameters. Setting a lower (higher) level for the parent (child) node, at first glance, may seem to favor a bigger tree. However, this may not necessarily be the case. Given the complex interactions between this option and other parameters, one can not easily predict the size of the tree. With all other options the same, however, one can confidently claim that, changing this option would affect the lower parts of the tree more than the upper parts.

**c) Penalty on Missingness:**

One of the CART methodology's superior features over standard techniques is that observations need not be dropped from the sample because of data non-availability. CART lists two other sets of splitters for each node along with the *primary splitter*, namely *competitor* and *surrogate* splitters. Competitors are the splitters making the second, third etc. highest improvement after primary splitters. Surrogate splitters, on the other hand, are those mimicking the action of primary splitter. They are used as back-up rules to split a case when its primary splitter value is missing. By employing the information contained in surrogates we can continue to classify these cases rather than dropping them from the analysis as would be necessary in a standard regression framework. It is worth noting, however, that keeping observations with missing values is not without cost. In general, the higher the number of missing values associated with a variable, the higher the chances that it becomes a primary splitter. This is because it is easier to make improvements with a variable that has many missing values. The missing value penalty option, then, adjusts each variable's *improvement score* depending on the extent of missing values associated with it. The effect of this penalty changes from node to node, in other words, it is node-specific reflecting the degree of missingness in the particular node. The formula used to adjust improvement scores in CART is as follows:

$$S=a*(\textit{ratio of non- missing cases in node } t)^b$$

The default settings of $a = 1$, $b = 0$ disable the penalty entirely; every variable receives a factor of 1. The closer b gets to 0 the smaller the penalty. Assigning 1 to both parameters would result in a one-to-one penalization of variables with respect to their degree of missingness. The sensitivity of the tree to this option is increasing in the degree of missingness. It discounts the improvement scores of explanatory variables upon which the selection of primary splitter is made. Different primary splitters at the top node mean a different distribution of observations on the left and right child nodes and hence a completely different tree.

**d) Best Tree:**

As mentioned above, the CART methodology chooses the optimal tree depending on the misclassification cost figures. The misclassification cost is computed as an average of the number of misclassified observations during 10 tests. CART reports a standard error figure of the misclassification cost as well. The default option, *minimum cost tree regardless of size*, uses the averaged figure in choosing the optimal tree. For a smaller (or even smaller) tree, one can set this option to *within mean plus one (or more) standard error of minimum cost tree*. This option serves to reduce the size of the tree and one can expect to see the same structure in the upper parts of the tree given the fact that it has no effect on the primary splitter selection.

**e) Misclassification Cost:**

This option is useful when misclassification of one class of observations is riskier than those of others. It is difficult to pin down its possible effects on the tree given its complex interaction with primary splitter selection phase but it is plausible to think that purer risky class nodes come at the expense of increased misclassification of other classes, and hence a higher overall cost tree. Default criterion treats all classes equally.

**f) Option Setting under EXIT and DGAPT Models**

The table below presents the option settings under EXIT and DGAPT models and their likely effect on the structure of the optimal tree.

**Table 1 Options**

| Option | EXIT Model (Classification Tree) | DGAPT Model (Regression Tree) | Default Setting | Sensitivity |
|---|---|---|---|---|
| ***Splitting Criterion*** | Entropy | Least Absolute Deviation | Gini and Least Squares | Low |
| ***Parent Node Size*** | 10 | 10 | 10 | Low |
| ***Child Node Size*** | 1 | 3 | 1 | Low |
| ***Missigness Penalty*** | 1.8 | 1 | No penalty | High (conditional) |
| ***Best Tree*** | Minimum cost tree | Minimum cost tree | Minimum cost tree | Low |
| ***Misclassification Cost*** | All classes count equally | All classes count equally | All classes count equally | High |

**ii. Maximal Tree Growing and Class Assignment**

This is the exploratory phase of the CART algorithm. The aim is to build the biggest tree possible to see the structure of the data. Splitting continues until no further improvement in purity is possible (see improvement formulas employed in Entropy and LAD splitting criteria above). This tree is called the maximal tree. The second step is to assign classes to the terminal nodes of the maximal tree. This is important because the misclassification rates can only be calculated after determining the class of terminal nodes. The class assignment is done depending on the "plurality" rule. Assume that we have a sample of 250 observations, 50 Class-A and 200 Class-B. The unconditional probability of being a Class-A (B) observation at the top node is 20% (80%). Class assignment of nodes is made depending on this figure. If, say, a terminal node contains 33% of Class-A observations, it is labeled as "Class-A Node". In the coming testing phase, if a Class-B observation will end up in this terminal node, it will be called as a misclassification.

Theoretically, at the end of this process one may reach a tree within which each individual observation is contained in a different node, an overfitting situation. Up to this point, nothing has been done to prevent outliers from becoming rules on the tree. If dataset contains outliers, the drive to reach the purest tree may result in attaining rules with thresholds determined at these outlier values. Note that if the aim were only to explain the data at hand, maximal tree could have been the best tree. But if one wants to use this tree to classify observations from a completely new dataset or from an expanded dataset (that is what "prediction" all about), the performance of this maximal tree will be a serious concern. It is clear that the applicability of such a tree to a new set of observations would be limited since it may contain outlier-induced rules which are not applicable to new cases. There should thus be a way to stop the tree growing before this occurs. There are certainly several ways to increase the applicability (hence robustness) of the tree, but the CART algorithm does this by testing different-sized subtrees (all obtained from maximal tree by cutting branches sequentially). It is at this point where the second segment kicks in.

**iii. Testing and Optimal Tree Selection**

The *generality-greedy* segment (known as testing phase) operates in exactly the opposite manner as purity-greedy segment does. It does so by getting rid of outlier-induced rules that can not be generalized, hence favoring smaller trees. In the testing phase, the sample is divided into two parts respecting the relative frequencies of different classes. The first part which constitutes 90% of the observations is used to grow a maximal tree, while the remaining 10% is used to test subtrees obtained from sequentially pruning the nodes of this maximal tree. This process is repeated 10 times so that each observation is used in the tree growing and testing phases. [4]

In each testing round, a maximal tree is grown, then it is pruned sequentially to form a pool of subtrees with different number of terminal nodes. After determining the calss assignment of each terminal node on these subtrees, the remaining 10% of data, testing subsample, is then used to test how correctly these nodes classify these testing observations. For each subtree group, the number of misclassified observations is calculated. The subtree with the least misclassification ratio is then chosen as the optimal tree.[5]

The selection of the optimal tree is thus based on the performance of subtrees under testing sample. The subtree containing fewer outlier-induced rules will obviously perform better in placing these test observations into nodes where they belong (i.e. crisis observation within crisis-prone node and vice versa). Figure 1 shows the evolution of misclassification ratio with respect to subtrees with different number of nodes. Starting from the maximal tree with 31 terminal nodes, we see that number of misclassified observations falls steadily as we move leftwards. After the subtree with 10 nodes, it starts to increase. And it is at this point we stop. The misclassification ratio bases the foundation of optimality criterion which resolves the trade-off between purity and generality. In short, the battle between these two opposing segments yields the tree within which purity and generality (applicability in other words) are optimized. It is called the optimal tree and by construction it will be robust[6] when applied to completely new datasets.

[4] Continuing with our example, in the testing phase CART divides the sample of 250 observations into two parts. 25 of them are reserved for testing and 225 for maximal tree growing. In both subsamples, class ratio of 1-4 is respected. That is, in testing subsample we have 5 Class-A and 20 Class-B observations, and in the maximal tree growing subsample we have 45 Class-A and 180 Class-B observations.

[5] See Appendix 2 for a detailed explanation of maximal tree growing and testing phases of the algorithm for the EXIT model.

[6] The testing phase of the algorithm ensures that, when this optimal tree is applied to a new set of observations, it will still yield the lowest misclassification rate compared to other subtrees (bigger or

## IV. CART Analysis

### IV.1 EXIT Model

In this model, the dependent variable is a binary EXIT variable, which takes a value of 1 if exit occurs at time t and 0 otherwise.

Our strategy consists of two steps. The first step is to identfy exit and no-exit prone nodes. Then, in a second step, we identify orderly and disorderly nodes depending on the output gap criterion.

The choice of dependent variable forces CART to group exit and no-exit countries under different nodes as purely as possible. Once *exit prone* nodes are identified, one can check whether *orderly* and *disorderly* exits have been concentrated within different nodes. It can be checked by comparing the mean output gap change across exit prone nodes. Before proceeding to the tree analysis, let us have a look at some descriptive statistics for the explanatory variables across exit and no-exit countries.

#### IV.1.1 Descriptive Statistics: Exit versus No-Exit

Table 2 presents the mean values of the explanatory variables across exit and no-exit groups in our sample. The choice of these variables has been done by CART, which orders variables in their splitting power either as a primary splitter or as a surrogate. The variables listed below portray statistically different means across the two groups of countries.

A year before exit, exiting countries compared to no-exiting countries typically face

- above-trend output growth,
- an overvalued real exchange rate,
- less openness,
- more frequent speculative pressure in foreign exchange market,
- a more flexible peg,
- a lower level of financial sector development,
- more incidence of exits in previous 12 months,
- higher inflation,
- higher US interest rates,
- shorter peg duration,
- lower long-term debt,
- lower public debt,
- lower total external debt,
- higher ratio of short-term debt to total debt,
- more frequent incidence of capital controls,
- a higher current account deficit,
- a worse budget balance, and
- above-trend real investment and real private credit growth.

However, having statistically different means does not necessarily guarantee representation on the tree. Starting from top to the bottom node, the variables making the best improvement are chosen as a primary splitter and others are kept aside as competitors. In parametric methods, on the other hand, it is the marginal effect of a variable that counts when others are held constant at their mean. Hence, the way in

---

smaller than the optimal tree) obtained from the maximal tree. Hence it will be robust to changes in the sample.

which a variable is chosen and represented as an explanatory variable is fundamentally different under parametric methods and CART**.** How do these technical differences affect the results? First of all, as long as CART finds a better splitter, some variables may not show up on the tree no matter how they differ across exit and no-exit cases. Differences across the means of exit and no-exit cases may vanish within a subgroup of exit and no-exit cases further along on the tree, removing representation of that variable on the tree. The opposite is also true, in that a variable may initially be found to be indistinguishable across exit and no-exit cases, but further down the tree, and depending on the splitters, it may significantly differ across some subset of observations and may become a splitter.

**Table 2 Descriptive Statistics: Exit vs. No-Exit**

| | **No-Exit** | | **Exit** | |
|---|---|---|---|---|
| **Variable** | ***Obs.*** | **Mean** | ***Obs.*** | **Mean** |
| Output Gap Change | *465* | 0.4 | *55* | -6*** |
| Overvaluation | *435* | -0.04 | *54* | 8.6*** |
| Output Gap | *465* | -0.11 | *55* | 3.7*** |
| Openness | *445* | 77 | *55* | 55*** |
| Speculative Pressure dummy | *395* | 0.13 | *53* | 0.6*** |
| Regime Flexibility | *377* | 5 | *51* | 25*** |
| Trade Balance | *452* | -4.49 | *55* | -4.76 |
| M2 to GDP | *393* | 51.8 | *53* | 40.3*** |
| M3 to GDP | *399* | 51.7 | *53* | 40.8*** |
| Liquid Liabilities | *373* | 50.94 | *50* | 42.94** |
| Incidence of Exits | *481* | 0.0346 | *56* | 0.04** |
| Inflation | *443* | 8.88 | *56* | 14.21** |
| Change in US interest rate | *481* | -0.04 | *56* | -0.04 |
| US Interest rate | *481* | 6.56 | *56* | 7.39* |
| Terms of Trade | *434* | 103.86 | *56* | 105.88 |
| Duration of Peg | *481* | 140 | *56* | 117** |
| Foreign Direct Investment | *456* | 1.68 | *55* | 1.43 |
| Long-term Debt | *267* | 48.35 | *41* | 36.3*** |
| Public Debt | *267* | 45.32 | *49* | 31*** |
| Change in Trade Balance | *450* | 0.11 | *55* | -0.45 |
| Short-term Debt to Total Debt | *270* | 13.06 | *41* | 21.6*** |
| Bank's Liquid Reserves to Assets | *437* | 12.49 | *55* | 13.64 |
| Capital Controls | *453* | 0.68 | *59* | 0.78* |
| Trade Concentration Index | *341* | 0.28 | *48* | 0.3 |
| Current Account Balance | *457* | -2.7 | *56* | -5.4*** |
| Domestic Credit | *419* | 55.94 | *49* | 50.01 |
| Domestic Credit to Private Sector | *437* | 46.4 | *55* | 43.02 |
| Total External Debt | *267* | 57.67 | *41* | 46.7** |
| Budget Balance | *425* | -3.26 | *52* | -3.39 |
| Change in Budget Balance | *399* | 0.07 | *50* | -0.9*** |
| Real Private Consumption Gap | *429* | -0.3 | *50* | 1.8 |

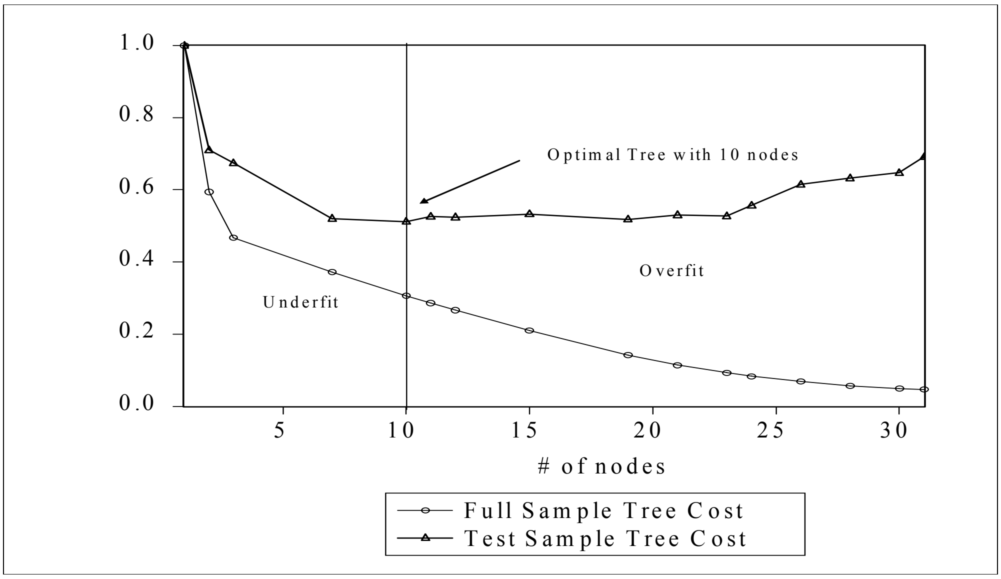
| | | | | |
|---|---|---|---|---|
| Real Gross Capital Formation Gap | *437* | -0.9 | *53* | 11*** |
| Real Private Credit Gap | *423* | -4 | *52* | 7*** |
| Private Consumption | *455* | 64.3 | *55* | 65.4 |
| Gross Capital Formation | *452* | 23.9 | *55* | 24.5 |
| Real Private Consumption Growth | *427* | 3.8 | *51* | 1 |
| Real Gross Capital For. Growth | *432* | 6.9 | *54* | 3.3 |
| Real Private Credit Growth | *434* | 8.5 | *54* | 6.2 |

Secondly, a variable may show up more than once (with different thresholds) on the tree so long as it continues to be the best splitter. From the first to the last node along the tree, there is a continuous race among variables to be a primary splitter, and races can run for an ever-decreasing number of observations. In parametric methods, however, variables are evaluated on their marginal contributions with all other variables being held constant at their mean value. If we use the same race analogy, there is just the one initial race for all observations. This is the main difference between CART and parametric methods. And it is this multiplicity that enables CART to detect non-linearities much more easily and effectively in comparison with parametric methods.

**IV.1.2 EXIT Tree**

Given the option settings, CART grows a maximal tree with 31 nodes as shown in Figure 4. The maximal tree has a misclassification cost of 4.7% and, as expected, fits the full sample with a higher degree of accuracy than any other subtree. But as mentioned above, unless verified by a testing procedure, this figure is misleading since the maximal tree by construction fits idiosyncrasies and noise within the full sample, which are unlikely to occur with the same pattern under the test sample. Indeed, when the test sample is applied to the maximal tree, we see that almost 70% of observations have been misclassified. Checking the costs under different subtrees, from right to left, till we reach the 10-noded tree, the number of misclassified observations decreases and after this point starts to increase again as given by the test sample cost curve in the figure.

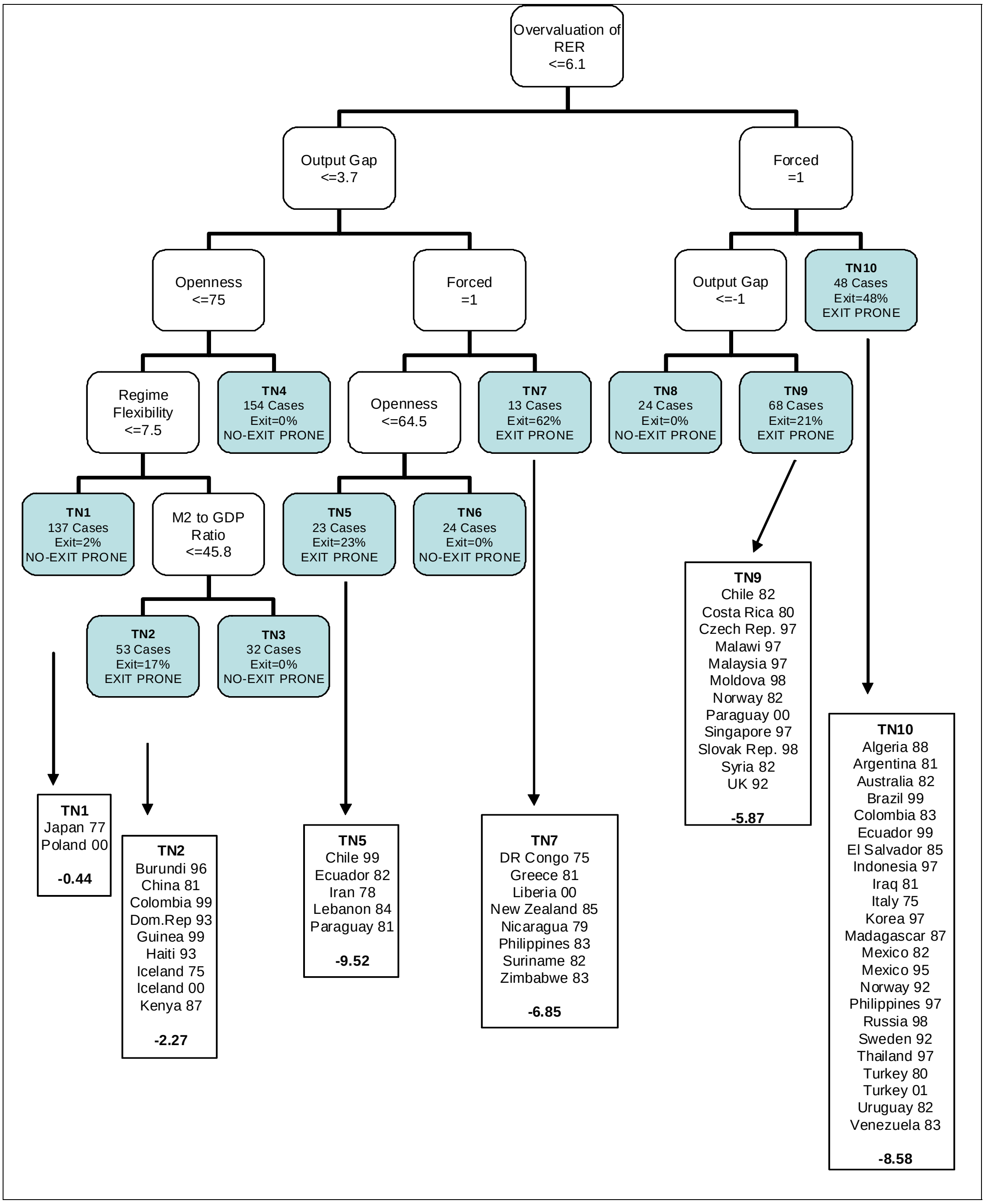
**Figure 4 Misclassification Cost under Full and Test Samples**




The optimal tree grown by CART has 10 nodes, and is presented in Figure 5. We have 59 exit and 507 no-exit cases in our sample, therefore unconditional probability of exit is around 10% (59/566). Recall that CART automatically labels terminal nodes "exit prone" and "no-exit prone" by comparing conditional exit probabilities in TNs with the unconditional exit probability in the top node. That is, TNs with exit probabilities *greater (smaller) than 10%* are labeled as *exit (no-exit) prone*. As a result, *TNs 2, 5, 7, 9 and 10 are labeled as exit prone* and *TNs 1, 3, 4, 6 and 8 as no-exit prone*.[7]

[7] Detailed explanation of CART procedure in growing EXIT tree is given in Appendix 2.

## Figure 5 EXIT Model Tree




Note: Figures below country lists represent the mean output gap change within the nodes.

Now let us trace back the routes leading to exit and no-exits.

The table below shows the set of conditions leading to the ten different TNs.

**Table 3 Terminal Node Information for the EXIT Model**

| TN No | Route | Surrogates | # of Cases | # of Exit | Conditional Exit Probability |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| **1** | Overvaluation<=6.1; Output Gap<=3.7; Openness<=75; Regime Flexibility<=7.5 | Lower duration and lower com. price index compared to TN2 and TN3 | 137 | 2 | 2% |
| **2** | Overvaluation<=6.1; Output Gap<=3.7; Openness<=75; Regime Flexibility>7.5;M2 to GDP<=45.8 | Higher inflation and lower dom. credit compared to TN3 | 53 | 9 | 17% |
| **3** | Overvaluation<=6.1; Output Gap<=3.7; Openness<=75; Regime Flexibility>7.5; M2 to GDP>45.8 | | 32 | 0 | 0% |
| **4** | Overvaluation<=6.1; Output Gap<=3.7; Openness>75 | | 154 | 0 | 0% |
| **5** | Overvaluation<=6.1; Output Gap>3.7; Forced=0; Openness<=64.5 | Lower public and long-term debt to GDP compared to TN6 | 23 | 5 | 22% |
| **6** | Overvaluation<=6.1; Output Gap>3.7; Forced=0; Openness>64.5 | | 24 | 0 | 0% |
| **7** | Overvaluation<=6.1; Output Gap>3.7; Forced=1 | Lower TOT and higher depreciation compared to TN5 and TN6 | 13 | 8 | 62% |
| **8** | Overvaluation>6.1; Forced=0; Output Gap<=-1 | | 24 | 0 | 0% |
| **9** | Overvaluation>6.1; Forced=0; Output Gap>-1 | Bigger decrease in TOT, higher increase in external debt, higher private credit compared to TN8 | 58 | 12 | 21% |
| **10** | Overvaluation>6.1; Forced=1 | Lower openness and higher depreciation before exit compared to TN9 | 48 | 23 | 48% |
| **Memorandum Items** | | | **Total** | **Exit** | **Uncond. Probability** |
| | | | 566 | 59 | 10.4% |

Findings can be summarized as follows:

***Exit Prone Nodes:***

**i. Overvaluation of RER increases the likelihood of exiting.**

The majority of exits occurred when the RER was overvalued. 35 out of 59 exits placed in TNs 9 and 10 experienced an overvaluation of the RER exceeding 6.1%.

An overvalued RER combined with

- speculative pressure increases the conditional probability of exit to 48% (TN10) [8]
- an output gap higher than -1% increases the conditional probability of exit to 21% (TN9).[9] In this node, on average, the output gap before exit is 4.5%.

In the absence of overvaluation

---

[8] Depending on their association value, **surrogates** can serve as a secondary source of information. For TN10, *openness* and *depreciation before* are given as surrogates and low openness (on average 44) and higher depreciation before exit (on average 27%) are features shared by many of exits in this node. Note that, average *openness* and *depreciation before* for exit cases in TN9 are 85 and 3.3% respectively.

[9] CART gives c*hange in terms of trade*, *change in total external debt* and *private credit* as the surrogates for TN9. Exit cases in TN9 can also be distinguished from cases in TN8 by having the negative terms of trade shock of 4.1, 5.5% increase in total external debt and 58% private credit on average. No-exit cases in TN8, however, saw their terms of trade to improve by 16, 1.7% decrease in their total external debt and had a private credit that is 30% of GDP on average.

**ii. a higher output gap in the previous year makes exit more likely.**

An output gap higher than 3.7% combined with

- *speculative pressure* increases the conditional probability of exit to 62% (TN7)[10]
- *openness* that is lower than 65 increases the conditional probability of exit to 23% (TN5).

In the absence of overvaluation and excess output growth,

**iii. Low openness and shallow financial markets combined with more flexible fixed regimes increases the likelihood of exiting**.

Countries with *openness* that is lower than 75% , shallower financial markets (*M2 to GDP* lower than 46%) and less rigid fixed regimes (*depreciation before* exit greater than 8%) are more prone to exit. Under these conditions, exit probability reaches 17% in TN2.[11]

***No-exit prone nodes:***

**iv. A lower output gap and greater openness make exiting less likely.**

Conditional on an *overvaluation of the RER* that is lower than 6.1%,

- The exit probability is less than 1% on average across TNs 1, 3 and 4 when the *output gap* is less than 3.7%,
- When the *output gap* is higher than 3.7%, it is *openness* that saves countries from exiting conditional on no *speculative pressure*. In TN6, the exit probability is 0% conditional on no speculative pressure and greater openness (higher than 65).

Conditional on a higher *overvaluation of the RER* (greater than 6.1%),

- The exit probability is 0% when the *output gap* is less than -1% and the country did not face *speculative pressure* in the previous 12 months (TN8).

### IV.1.3 Orderly versus Disorderly Exit

After identifying different routes leading countries to exit, the next step is to rank these groups of exits depending on the output gap change. As mentioned earlier, we expect CART to place orderly and disorderly exits into separate TNs, so that we can identify routes leading to "orderly" and "disorderly" exits. To that end, first of all, we test how significant the difference is between group means (of exit cases) by using a mean t-test with unequal variance.

**Table 4 Mean Difference t-test of Output Gap Change: EXIT Model**

| Exit Probability | | 2 % | 17 % | 0 % | 0 % | 23 % | 0 % | 62 % | 0 % | 5 % | 48 % |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Node | TN1 | TN2 | TN3 | TN4 | TN5 | TN6 | TN7 | TN8 | TN9 | TN10 |
| 2 % | TN1 | | | | | | | | | | |

[10] *Terms of Trade* and *depreciation before* are two variables given as surrogates and cases in these nodes can also be distinguished by lower Terms of Trade (on average 87) and higher depreciation rates (on average 45%) before exit.

[11] *Inflation* and *domestic credit* variables are given as surrogates for TN2. Most of the cases placed in TN2 can also be distinguished by having higher inflation rates, on average 14%, and lower domestic credit (on average 40% of GDP) as opposed to no-exit cases placed in TN3, for which the variables took values of 7.2% and 82% respectively.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 17 % | TN2 | -1.8 | | | | | | | | |
| 0 % | TN3 | | | | | | | | | |
| 0 % | TN4 | | | | | | | | | |
| 23 % | TN5 | -9.1** | -7.3** | | | | | | | |
| 0 % | TN6 | | | | | | | | | |
| 62 % | TN7 | -6.4* | -4.6* | | | 2.7 | | | | |
| 0 % | TN8 | | | | | | | | | |
| 21% | TN9 | -5.5* | -3.6* | | | 3.6 | | 1 | | |
| 48 % | TN10 | -8.1** | -6.3** | | | 0.9 | | -1.7 | | -2.7 |

Note: Figures show the mean difference between nodes (row node minus column node). *** indicates statistically different means at 1% significance level, ** at 5% and * at 10%.

The test results show that it is indeed possible to group TNs into *orderly* and *disorderly* nodes. Across these groups, the mean *output gap change* value differs significantly, and differences vanish across same type of nodes. Take for example TN1 and TN2. Both are labeled as orderly and there is no statistically significant difference between the mean output gap change. Comparing orderly TN2 and disorderly TN10 -a 6.3% difference is statistically significant at 5% significance level.

A second check can be done by comparing *exchange rate depreciation* figures across orderly and disorderly nodes. In fact, this portrays different evolutions for the two groups of exits. The mean depreciation rate within orderly nodes is only 24%, whereas in disorderly nodes it increases to 81%. This fact also reinforces our observation that the majority of countries do exit in the midst of a turbulence which has negative consequences in terms of exchange rate depreciation as well as output growth.

These findings indicate that most of the cases placed in TN1 and TN2 managed a relatively smooth transition between regimes compared to the 47 cases placed in TN5, TN7, TN9 and TN10. *We thus identify TN1 and TN2 as orderly nodes and the others as disorderly.*

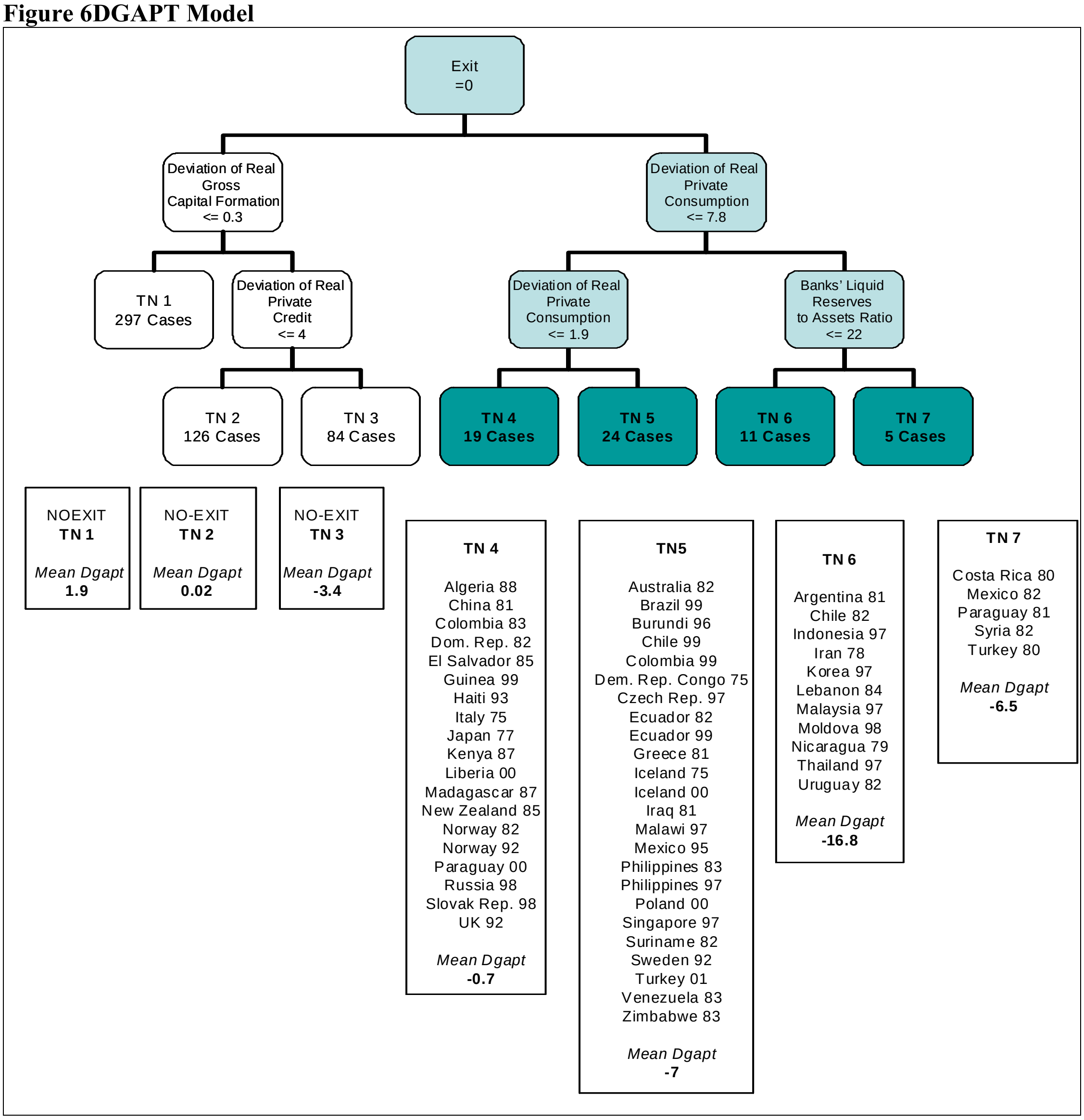
### IV.2 DGAPT Model

In this section, we would like to analyze the regression tree grown using a continuous dependent variable, namely the *output gap change* (*dgapt*). The CART algorithm tries to group countries with a similar evolution in the output gap change within the same terminal nodes. As in classification tree analysis, CART first grows the maximal tree. Within-node median, minimum and maximum values of the dependent variable are calculated for each terminal node. Then, in the testing phase, CART tries to place test sample into the nodes of different subtrees which have been obtained through pruning maximal tree. If the observation in the test sample falls outside the boundaries drawn by the min and max values of that particular node, it is said to be misclassified.

Turning then to the DGAPT tree, we find that the optimal tree has 7 nodes with a misclassification cost of 95%. Compared to the EXIT model, the DGAPT tree does not perform well in classifying observations in the right nodes as evidenced by high misclassification cost. Nevertheless, our tree reveals some interesting points worth mentioning.

First of all, CART starts splitting cases by picking the binary *exit* variable as a primary splitter in the very top node, showing the importance of an exit event on output gap evolution. Note that for the whole sample, the output gap change takes, on average, a value of -0.2%; it is -6% for exit cases and 0.4% for no-exit cases.

**Figure 6DGAPT Model**




Secondly, CART grows the tree to unveil an important link between the financial and real sectors. Notably, deviation of private credit, private consumption and investment from their H-P trends are chosen as the most important variable,s either as primary splitters or surrogates. In other words, these variables have the most power in explaining the change in output gap; we return to this issue below.

As in the EXIT model, we can determine the type of nodes depending on the mean output gap change. From the table below we see that only TN4 with a mean output gap change of -0.7% can be identified as an *orderly* node. Accordingly, TN5, TN6 and TN7 are assigned as *disorderly* nodes. Median depreciation rates also support this distinction. These are 23% in TN4 as opposed to 56% across TN5-TN7.

**Table 5 Mean Difference t-test of Output Gap Change: DGAPT Model**

| **Terminal Node** | TN4 | TN5 | TN6 | TN7 |
|---|---|---|---|---|
| TN4 | | | | |
| TN5 | -6.3*** | | | |
| TN6 | -16.2*** | -9.8*** | | |
| TN7 | -5.8*** | 0.6 | 10.4*** | |

Note: Figures show the mean difference between nodes (row node minus column node).
*** indicates statistically different means at 1% significance level.

Before exploring the routes on the tree let us have a look at what the descriptive statistics tell us about the cases gathered in orderly and disorderly nodes. Table 7 shows the mean difference of explanatory variables across orderly and disorderly nodes under each model.

The exit cases in our orderly TN4 can be distinguished from other exits in disorderly TNs in that they have

- a lower output gap,
- a lower extent of depreciation (hence more rigid pegged regime),
- lower inflation,
- a bigger improvement in trade balance,
- a higher current account balance,
- a lower private consumption gap around trend growth,
- a lower gross capital formation gap around trend growth,
- a lower private credit gap around trend growth,
- lower private credit growth, and
- higher public debt before exit.

Also, exits in the orderly node TN4 occurr when the US interest rate is lower.

Coming to our DGAPT tree, the table below shows the route information of 4 nodes where exit cases have been gathered.

**Table 6 Terminal Node Information for DGAPT Model**[12]

| | | | | **Output Gap Change** | | |
|---|---|---|---|---|---|---|
| **TN No** | **Route** | **Surrogates** | **Cases** | **Mean** | **Median** | **Min/Max** |
| 4 | Deviation of Real Private Consumption <=1.9 | Higher improvement in current account balance and lower deviation of investment compared to TN5 | 19 | -0.7 | -0.9 | -6.9/8.7 |
| 5 | 1.9 < Deviation of Real Private Consumption <=7.8 | | 24 | -7 | -5.2 | -54.7/1.5 |
| 6 | Deviation of Real Private Consumption >7.8; Banks' Liquid Reserves to Assets <=22 | Higher exports to imports, lower inflation and higher domestic credit to private sector compared to TN7 | 10 | -16.8 | -17.5 | -22.9/ -10.8 |
| 7 | Deviation of Real Private Consumption >7.8; Banks' Liquid Reserves to Assets >22 | | 5 | -6.5 | -5.9 | -10.7/-4 |
| **Memorandum Items** | | | | | | |
| **Top Node** | | **Exit=1** | 58 | -6.6 | -5 | -54.7/8.7 |
| | | **Exit=0** | 487 | 0.55 | 0.5 | -21.5/47.5 |

As seen, the most powerful variable distinguishing orderly exits from disorderly ones is the *private consumption gap* (deviation of real private consumption from its H-P trend).

**i. Above-trend consumption and investment growth lead to disorderly exits.**

Countries with *real private consumption deviation* lower than 1.9% are likely to exit in an orderly fashion (TN4). *Deviation of investment* from long-term trend, *current account* and *trade balance* are variables given as surrogates for TN4. And orderly exits in TN4 can also be distinguished by having *lower deviation of investment, higher improvement in current account* compared to disorderly exits in TN5.

**ii. More liquid banking system can soften the negative consequences of disorderly exits on the output gap.**

Although most of the exits in TN6 and TN7 are of a disorderly type, countries in TN7 experienced a less dramatic change in their output gap (-6.5% vs. -16.8% on average whose difference is significantly different from zero). And *banks' liquid reserves to asset ratio* is the variable that makes the difference. Countries with a more liquid banking system (TN7) do relatively well in curbing the transmission of volatility from consumption and investment to output.

Checking the grouping of cases in different TNs, we see that exits in TN7 are those that occurred during *Balance of Payment* type crises of 80s. *Inflation*, *exports to imports ratio and domestic credit private sector* are variables given as surrogates for the parent node preceding TN6 and TN7. That is, exits in TN6 have

[12] Table shows information on nodes containing exit cases only. Terminal nodes 1-3 contain no-exit cases.

lower inflation, higher exports to imports ratio and higher domestic credit compared to cases in TN7. It is also interesting to see that many of the *Asian Crises* countries have been placed in TN6 where banking sector fragility is present as pointed out by the primary splitter.

### IV.3 Combined Analysis of EXIT and DGAPT models

41 out of 59 (70%) exits have been classified as orderly and disorderly (6 orderly and 35 disorderly exits) by both models. The *mean differences* between orderly and disorderly groups are given in the table below under the column COMBINED. Once we restrict our analysis to these cases we see that, orderly exits occurr when there is:

- lower overvaluation,
- a lower output gap,
- less openness,
- a more rigid pegged regime,
- less foreign direct investment,
- a better improvement in trade balance,
- a higher current account balance, and lower short-term to total debt,
- a lower private credit, consumption and investment gap around the long-term trend and, lower private credit growth a year before exit.

Significantly, *higher output gap*, *higher credit*, *consumption* and *investment growth* coupled with significant *overvaluation of the RER* before exit are the most important characteristics of most countries placed in disorderly nodes under both models. **All of these variables show a sharp deterioration in the year following exit.** Credit, investment and consumption fell below long-term trend growth, output collapsed, RER depreciated dramatically.

**Table 7 Descriptive Statistics: Orderly vs. Disorderly Nodes under Models**

| | MODELS | | |
|---|---|---|---|
| **Variable** | **EXIT†** | **DGAPT** | **COMBINED** |
| Output Gap Change | 5.7*** | 8.8*** | 9.4*** |
| Overvaluation | -16*** | -5.3 | -17.6** |
| Output Gap | -5.4*** | -4.4** | -7*** |
| Openness | -19.2** | -15.4 | -31** |
| Speculative Pressure dummy | -0.6*** | 0.04 | -0.32 |
| Regime Flexibility | -0.7 | -12.8* | -15* |
| Trade Balance | -1.1 | 2.4 | 1.8 |
| M2 to GDP | -4.3 | 6.4 | 3.2 |
| M3 to GDP | -3.7 | 5.7 | 5.1 |

| | | | |
|---|---|---|---|
| Liquid Liabilities | -2.1 | 12.6 | 13.5 |
| Incidence of Exits | -0.01 | -0.01 | -0.01 |
| Inflation | -1.2 | -6.6* | -6.9* |
| Change in US interest rate | -0.05 | -0.12 | -0.18 |
| US Interest rate | -1.4 | -1.5* | -1.3 |
| Terms of Trade | -5 | -5 | -6.8 |
| Duration of Peg | 32 | -11 | 21 |
| Foreign Direct Investment | -0.8 | -0.8 | -1.6*** |
| Long-term Debt | 13.7 | 24.3 | 17.7 |
| Public Debt | 14.7 | 25.7* | 23 |
| Change in Trade Balance | 0.7 | 2.2** | 2.2* |
| Short-term Debt to Total Debt | -10** | -6.4 | -10.5* |
| Bank's Liquid Reserves to Assets | 4.7 | 4.4 | 15.1 |
| Capital Controls | 0.27*** | 0.25*** | 0.34*** |
| Trade Concentration Index | 0 | 0.03 | 0 |
| Current Account Balance | 1.4 | 2.5* | 3.4* |
| Domestic Credit | -5.4 | 7.5 | 3.5 |
| Domestic Credit to Private Sector | -3.3 | 0.6 | -0.5 |
| Total External Debt | 5.3 | 41.3 | 17 |
| Budget Balance | 0.05 | -1.2 | -1.1 |
| Change in Budget Balance | 0.8 | 0.3 | 0.7 |
| Real Private Consumption Gap | -0.5 | -19.1* | -10.7*** |
| Real Gross Capital Formation Gap | -15.2** | -14* | -24.7** |
| Real Private Credit Gap | -3.6 | -9.7** | -9.6*** |
| Private Consumption | 7 | 4.3 | 9.5 |
| Gross Capital Formation | -2.1 | -2.7 | -2.9 |
| Real Private Consumption Growth | 2.5 | -15.7 | -1.3 |
| Real Gross Capital Form. Growth | -9.4 | -3.4 | -13.7 |
| Real Private Credit Growth | -4.2 | -5.3* | -7.9* |

† ORDERLY nodes' mean **minus** DISORDERLY nodes' mean in EXIT, DGAPT. COMBINED contains cases which are classified as same by both models. See Table A.III.3 in the appendix.
Mean difference t-test with null hypothesis of equal mean; *** significant at 1%, ** 5%; * 10%.

What are the dynamics behind such excessive volatility in the economy? In the following section we will try to answer this question.

### IV.3.1 Boom-Bust Cycles behind Disorderly Exits?

There is a strong link between financial development and growth. A large body of literature claims that it is financial development that stimulates economic growth, in other words, causality runs from the former to latter (see Levine (1997) for an early survey of literature). Keeping this in mind, then, it becomes natural to seek the roots of output volatility in developments that take place in the financial side of the economy.

Two strands of the literature, *financial liberalization* and *macroeconomic stabilization,* cite lending booms as one of the most important factors behind currency and banking crises. Now let us see to what extent the stylized facts can explain the volatility behind disorderly exits in our sample. In other words, is it less painful to exit during the pre-liberalization period than during the post-liberalization period? And secondly, what are the chances of stabilizing the economy without incurring output and exchange rate collapse in the medium-term?

### i. Financial Liberalization and Volatility:

Studies on financial liberalization suggest that countries with liberalized financial markets grow faster. By decreasing the cost of funding, liberalization increases the amount of credit invested and as more investment projects are undertaken, risk diversification through financial markets becomes easier, which in return stimulates investment. The other side of the coin, however, is the increased occurrence of crises following financial liberalization. The crisis literature highlights the detrimental effect of excessive credit growth in countries where liberalization has been undertaken inadequately and left unchecked. See for example Demirguc-Kunt and Detragiache (1998) and Kaminsky and Schmuckler (2002), Wyplosz (2002). In their study Tornell and Westermann (2002) investigate the effect of lending booms preceding twin crises. They find that lending booms coincide with overvaluation of the RER and faster growth of the nontradables (N) compared to the tradables (T) sector. Their analysis shows that '…comovements are generated by the interaction of two characteristics of financing typical of middle income countries: risky currency mismatch and asymmetric financing opportunities across the N and T-sectors'.

Poorly regulated financial liberalization may lead to a lending boom following a surge in capital inflow that boosts domestic investment and consumption. Implicit or explicit bail-out guarantees, inadequate monitoring of new projects, among other factors, play crucial roles in feeding lending booms through the credit channel, or through a financial accelerator channel as mentioned by Bernanke et al. (1999), Aghion et al. (2004). Asset price increases during a boom increase borrowers' net worth which facilitates new lending. Increased demand for assets push asset prices even higher, a bubble which bursts as the bust period sets in.

Is it possible to say that disorderly exits occur mainly in the post-liberalization period triggered by a lending boom that follows? What is the distribution of exits in relation to liberalization dates?

Bekeart, Harvey and Lundblad (2005) provides the most extensive dataset on financial liberalization. They identify the date for financial liberalization as the issuance of the first American Depository Receipt.[13] In our original dataset we have 59 exits, of which 51 coincide with data on financial liberalization. If we cross-check exits with the dates for financial liberalization, we find out that **more than half of all exits** take place **before financial liberalization** (57%, 29 out of 51). In line with the literature, which predicts a higher probability of crisis in the post-liberalization period, 86% of exits (19 out of 22) which occurred during post-liberalization period were placed in one of the disorderly nodes under our EXIT model.[14]

---

[13] See Bekeart et al. (2005).

[14] Under DGAPT model, this figure becomes 77% (17 out of 22 exits in the post-liberalization period).

As we compare mean output gap change figures for exits occurred during pre and post-liberalization periods we reach the same conclusion, namely output volatility around exit year is significantly higher during post-liberalization than that of during pre-liberalization episode.[15]

**ii. Macroeconomic Stabilization Programs and Volatility**

There are several reasons for countries to adopt fixed exchange rate regimes. Macroeconomic stabilization is one of these. Use of the exchange rate as a nominal anchor to stabilize chronic inflation constitutes the main instrument in exchange-rate-based stabilization (ERBS) programs which have been widely adopted especially by Latin American countries.

Macroeconomic stabilization programs are, however, often criticized on the grounds that they lead to excess volatility in the economy. For example, less-than-perfectly-credible exchange rate stabilization programs may trigger a consumption boom as agents increase their demand for consumption or investment goods when these are ‘‘cheap’’, in other words, before the possible collapse of the currency. The economic consequences of stabilization programs using exchange rate or monetary aggregates as nominal anchors have been widely studied in the literature - see for example Calvo and Vegh (1999), Tornell and Westermann (2002), Hamann et al. (2005) and Ranciere et al. (2005). One of the stylized facts to emerge from country experiences is that economies often exhibit a “boom-bust cycle”, in which the boom period is often terminated by a crisis and an eventual recession. Overvaluation of the RER, an unavoidable consequence of having a peg in an economy where the upward pressure of high inflation can not be offset by an increase in productivity, plays a pivotal role in this outcome. Hamann et al. (2005) lists stabilization programs implemented during 1960-2001 period. They define a stabilization episode as a period of substantial decline in inflation from a relatively high and persistent level which lasts at least 24 months. Stabilization is said to start at time T if the significant decline in inflation begins in that month and does not revert back for at least 11 consecutive months.[16]

Comparing this data with our own sample, we find that 9 of exit cases represent an exit from stabilization programs which have been identified by the abovementioned study, 8 exits from ERBS program and 1 from money based stabilization programs.[17] 8 out of 9 exits from stabilization programs have been placed in disorderly nodes by both EXIT and DGAPT models, verifying the criticisms mentioned above. In general, an output boom is accompanied by real exchange rate overvaluation and many of them faced speculative pressure ahead of exit. For these cases, the output gap a year before exit,

[15] The difference of mean output gap change is statistically different than zero under 5% significance level.

[16] For more information on episode determination and list of programs with historical records see Hamann et al. (2005).

[17] Exchange rate based stabilization programs with their starting dates are as follows: Argentina December 1978, Brazil July 1994, Chile February 1978, Ecuador September 1993, Iceland March 1984, Mexico September 1988, Turkey December 1999, Uruguay October 1978. Money based stabilization program Malawi January 1995. See Hamann et al. (2005) and Calvo and Vegh (1999) for historical records of stabilization episodes.

on average, reached 5.9% above trend followed by a contraction of -3.5% with a depreciation of 121% following the exit year. Note that for other exits, these values are 4.4%, -1.9% and 64% respectively.[18] Regarding output volatility, as stylized facts suggest, private credit plays an important role. In the next section we will investigate the link between private credit and output growth.

### IV.3.2 Credit and Output Boom

In theory, credit can grow as a result of financial deepening (trend), normal cyclical upturns or excessive cyclical movements (called as credit booms). As mentioned earlier, credit booms play an important role in the making of most of the crisis episodes. Recognizing the fact that most exits take place in the midst of a crisis raises questions as to the role credit plays. Excessive credit growth may be the factor behind the unsustainable rise of the output gap a year before exit - this is what we would like to investigate in this section.

WEO (2004) analyses credit expansion episodes in 28 emerging market countries between 1970 and 2002. The study finds that cyclical upturns in economic activity are associated with credit booms followed by a deep contraction in output and private absorption. The price of nontradables increases relative to tradables during credit booms and falls subsequently. Banks expand credit (mostly to the N-sector), financed mainly by increased external borrowing. The ratio of debt to equity in the N-sector rises faster and is higher than that of the T-sector, reflecting the liability dollarization phenomenon.

Noting the fact that credit can grow faster than GDP as an economy develops, a process known as financial deepening, the study makes a distinction between episodes of *rapid credit growth* and *excessive credit growth (credit booms).* A *credit boom* episode is identified as an episode of credit expansion exceeding the standard deviation of that country's credit fluctuations around the trend by a factor of 1.75. Real private credit (private credit deflated by CPI) is detrended by H-P filter, and since by construction the mean of fluctuations around the trend is expected to be zero, using a threshold with 1.75 standard deviation suggests that the probability of observing credit booms is 5% .

Episodes of *rapid credit growth*, on the other hand, are identified based on the evolution of real credit growth in the years preceding credit booms. For 28 emerging market economies, the study finds that the median rate of real credit growth preceding credit booms is 17%, and that episodes with an average real credit growth over three years exceeding this threshold are labeled as rapid credit growth.

Following the same methodology for 133 countries between 1970 and 2004, we find 116 episodes of credit boom. The median rate of real credit growth preceding credit boom episodes is found to be 12.5%. Using this threshold, we identify 232 episodes of rapid credit growth. 73 of these episodes end in a credit boom whereas the remaining 159 episodes represent normal cyclical movements of credit. After identifying the peak year of the credit boom and rapid credit growth episodes, we check how these peak years are distributed around the exit year. Most of the credit boomers saw their credit peak in the year of exit, t=0. Countries with rapid credit growth episodes, also saw their credit growth peak mostly at t=0 and some at t-1, a year before exit. In event study analysis, this timing issue is important for expositional purposes. For

[18] Mean of output gap at t+1 and depreciation rate across exits from stabilization programs and other exits are statistically different at 10% significance level.

this reason, we group countries (i.e. boomers having a peak during the exit year) so as to have a clearer view of evolution of some selected variables around the exit year. We have 59 exits in our sample with 11 of them placed in orderly and 48 in disorderly nodes.[19] The most reasonable distribution of episodes across exits placed in these nodes is as follows :

*Group 1 : Credit Booms associated with disorderly exits.*

10 exits in disorderly nodes have been preceded by a credit boom episode with a peak taking place at t=0, the exit year.

*Group 2 : Rapid Credit Growth associated with disorderly exits.*

12 exits in disorderly nodes have been preceded by a rapid credit growth episode with a peak at either t-1 or t=0.

*Group 3 : Disorderly exits without Boom or Credit Growth.*

16 exits in disorderly nodes have experienced neither credit boom nor rapid credit growth episodes between t-4 and t=0.

*Group 4 : Orderly exits without Boom or Credit Growth.*

9 exits in orderly nodes have experienced neither a credit boom nor rapid credit growth episodes between t-2 and t=0.

A list of exits under these groupings can be found in Table A.III.3 in Appendix 3.

The **comovement** of *credit* with *output*, *consumption* and *investment* for exit cases in Group 1 is highly visible in the first column of Figure 7. The same is true for Group 2 cases which experienced rapid credit growth, yet the amplitudes of cycles are smaller. Note that all of the exits in these groups have been placed in one of the disorderly nodes. For both groups, event study analysis indicates that it may be **excessive credit expansion** (either in the form of credit boom or in rapid credit growth) which leads to the output boom through higher private investment and consumption expenditures.

In Group 3, none of the countries experienced credit boom nor credit expansion episodes around the exit year. Private credit, consumption and investment gaps are hardly different from zero. The change in output gap is relatively small compared to Group 1 and 2 but it is nonetheless -4.5% on average and that is why they have been classified as disorderly. **The link between credit and output is missing for these cases.** Note that in only 5 of the 16 cases did countries liberalize their financial markets before exiting, and this is in line with our argumentation above on the disruptive short-term effect of liberalization.

[19] Note that for the sake of brevity, here we made groupings based on EXIT model's results. Same figures have been reproduced for the groupings under DGAPT model and presented in Figure A.III.2 in Appendix.

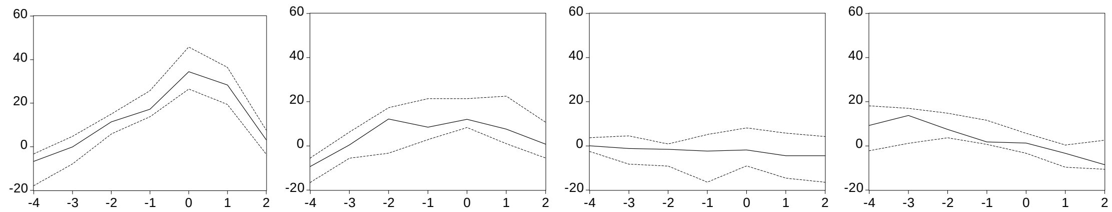
**Figure 7EXIT Model: Selected Variables around Exit time**
(% deviation from H-P trend)

**Bold line** : Median **Dashed lines** : Upper and lower quartiles

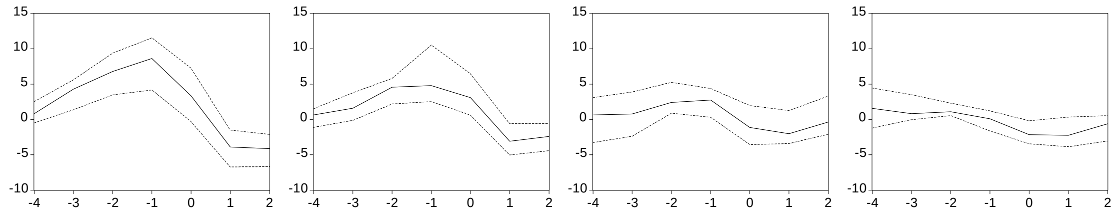
DISORDERLY TNs | ORDERLY TNs

*1. Credit Boom* *2. Rapid Credit Gr.* *3. No Boom/Gr.* *4. No Boom/Gr.*

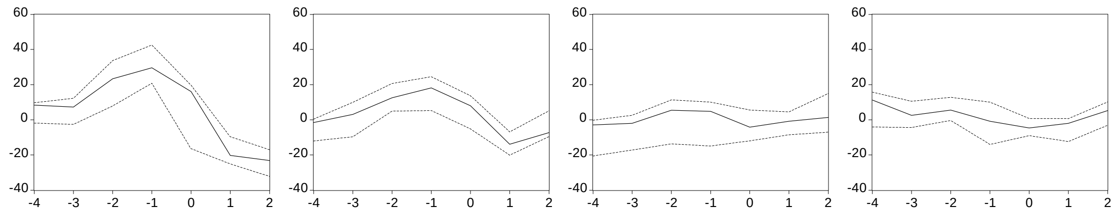
***Real Private Credit***



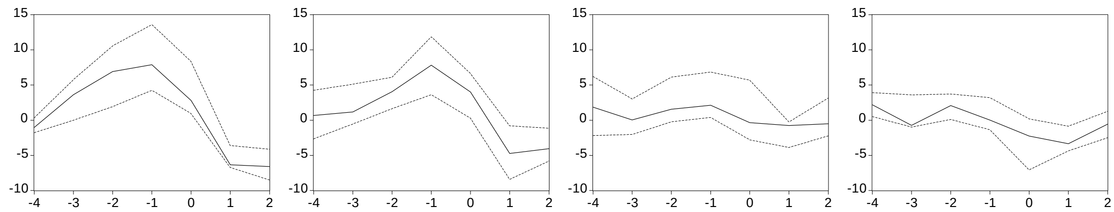
***Real Output***



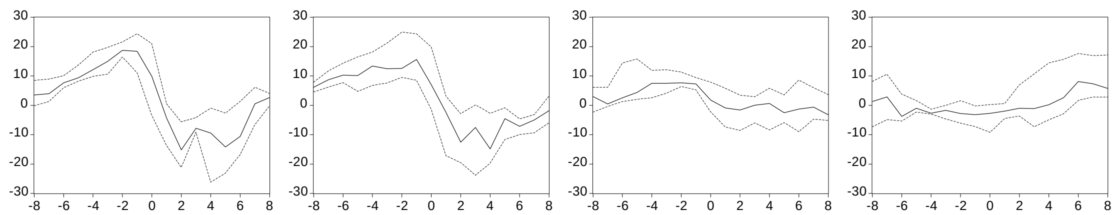
***Real Private Investment***



***Real Private Consumption***



***Real Exchange Rate***



Note : The upper (lower) quartile is the smallest (largest) value of the highest (lowest) 25 percent of all observations in each year (quarter for real exchange rate series). Orderly nodes under EXIT model are TN1 and TN2, disorderly nodes are TN3, TN5, TN7, TN9 and TN10. See Table A.III.3 for country groupings.

What are the sources of volatility in output then? Speculative pressure is one. 10 out of 16 exits in this group faced speculative pressure ahead of exit. Russia's 1998 and Brazil's 1999 exits can be explained by contagion. And, debt problems are apparent behind Ecuador's 1982, Colombia's 1983 exits. But what is clear is that credit growth does not lie behind the collapse of output for this group of countries.

Group 4 involves exits placed in orderly nodes. Evolution of variables around the trend is flat and can not be distinguished from zero. None of the countries experienced credit boom nor rapid credit expansion episodes. One interesting observation is that 8 out of 9 orderly exits have been managed during pre-financial liberalization period. And capital controls were intensively at their disposal (except Japan's 1977 exit) by the time of exit.

**IV.4 Results of Non-parametric Part**

Our results show that overvaluation and an unsustainable high output gap coupled with private credit and consumption gaps are the most important factors determining the type of exit, i.e. orderly or disorderly. As argued by Eichengreen and Masson (1998), it is better to exit early than too late before the above-mentioned vulnerabilities take hostage of the peg. Our results indicate that the sources of these vulnerabilities can be found and understood within the framework of ill-managed financial liberalization and macroeconomic stabilization.

Our results also suggest that less rigid pegs are more prone to exit than hard pegs, in a way highlighting the credibility and stability enhancing features of hard pegs, as suggested in the hollowing out hypothesis *a la* Fischer (2001).

The Optimum Currency Area literature argues that countries with a high degree of integration (hence more open) are more likely to have pegged regimes, since stable rates enhance the welfare gains derived from trade. See, for example Levy-Yeyati et al. (2006). Verifying this theory, we find that countries with less trade openness are more likely to exit. A greater degree of openness, on the other hand, increases the vulnerability of countries to external shocks, notably to terms-of-trade shocks. In our EXIT tree, we find that, among the countries with higher openness, countries facing terms-of-trade shocks are more likely to exit (see TN7 and TN9 for example).

Following the Asian crises in 1997, the structure of the financial sector was increasingly recognized as a significant element. The size of currency and maturity mismatches, the liquidity of banking sector are among the variables that researchers have found to be important in understanding the dynamics of third generation currency crises - see for example Chang and Velasco (2000) and Levy-Yeyati et al. (2006). In this paper, we used *Banks' Liquid Reserves to Assets ratio* as an indicator for the health of the banking sector, since more refined data, say on liability dollarization, is not available for the majority of the countries in our sample. Our results support theory. In the DGAPT tree, we find that countries with a high reserve to assets ratio in the banking sector experience relatively less painful post-exit realization of output, thanks to the decreased amplitude of the output cycle (see TN7). A *speculative pressure index* was constructed so as to detect the pressure in the year to exit and can be used as a proxy indicating the size of the vulnerability caused by currency and maturity mismatches. Countries with sizable currency and maturity mismatches are expected to be more vulnerable to changes in the nominal exchange rate and the interest rate. As expected, almost all of the exits which were followed by a period of speculative pressure were disorderly, showing the importance of these vulnerabilities which carry the potential of triggering a crisis when conditions turned unfavorable.

**IV.5 Robustness Checks**

In this part we would like to present two sets of robustness checks.

The first set employs the built-in "scoring" device of CART. It is used to classify new observations (belonging to 2001-2004 period) on the tree which is grown using the original sample (covering 1975-2001 period). CART trees are by construction robust, guaranteed by the testing phase. One can fairly be sure about the likely size of misclassification by looking at the misclassification ratio of the optimal tree.

Option setting affects the size and structure of the tree. Another check can be made upon the sensitivity of EXIT tree to changes in the parameter (option) settings.

**IV.5.1 Scoring**

The robustness of our EXIT and DGAPT tree will be checked with the expanded dataset covering the 1975-2004 period. This new dataset is obtained by appending the regime classification of Eichengreen and Razo-Garcia (2006) to the existing R&R(2004) classification. Applying the three-year window and dropping currency union cases leaves us with 650 observations, 68 exits and 582 no-exit cases. In the next two sections we check how correctly these 9 new exit cases will be classified on our EXIT and DGAPT trees.

**i. EXIT Model**

The table below shows the classification of new exits under the EXIT model. Note that the misclassification (exit case in a no-exit prone node and vice versa) cost of our EXIT tree is 51.2% (35.6% of exit cases plus 15.6% of no-exit cases). That is, half of the observations have been misclassified by the tree during the testing phase. Once we score our expanded dataset on our tree, we see that 5 out of 9 new exits have been classified incorrectly. At first sight this is quite disappointing. But we know from our EXIT model that there are exits which were placed within no-exit prone nodes, i.e. 2 orderly exits in TN1. In the end, our aim is to separate orderly exits from disorderly ones. From such a perspective, the placement of orderly exits within no-exit prone nodes may not be taken as misclassification. In this case, the number of misclassified exits is reduced to 4.

**Table 8 Classification of New Exits under the EXIT Model**

| Country | Time | Output Gap Change* | Depreciation* | Terminal Node** | Performance: Exit/No-Exit | Performance: Orderly/Disorderly |
|---|---|---|---|---|---|---|
| Argentina | 2002m2 | -3.6 | 258 | EP TN10 | Correct | Correct |
| Botswana | 2004m2 | na | -5 | EP TN9 | Correct | Incorrect |
| Gambia | 2002m8 | -3.9 | 39 | NEP TN4 | Incorrect | Incorrect |
| Kyrgyz Rep. | 2003m1 | 6.7 | -5 | NEP TN4 | Incorrect | Correct |
| Moldova | 2002m11 | 9.2 | 4 | NEP TN4 | Incorrect | Correct |
| Myanmar | 1983m5 | 4.5 | 6 | EP TN7 | Correct | Incorrect |
| Uganda | 2002m2 | 0.2 | 3 | NEP TN1 | Incorrect | Correct |
| Uruguay | 2002m7 | -8.5 | 98 | EP TN10 | Correct | Correct |
| Zimbabwe | 2003m3 | na | 1402 | NEP TN1 | Incorrect | Incorrect |

| | | |
|---|---|---|
| **Memorandum Items:** | | |
| **Orderly nodes' mean** | -1.9 | 24 |
| **Disorderly nodes' mean** | -7.7 | 81 |

*Output gap change between t-1 and t+1. Depreciation between 6 months before and after exit.
** EP: Exit prone, NEP: No-exit prone

**ii. DGAPT Model**

- Recall that the optimal DGAPT tree has a misclassification cost of 95%. In other words, 95% of the observations were misclassified during the testing phase. In regression tree analysis, where the dependent variable is continuous, the misclassification takes a different form. Here, a case is said to be misclassified if the value of dependent variable of that case falls outside the boundaries of the node given by the minimum and maximum observations. Table 9 shows that, overall, 3 out of 7 (excluding 2 indeterminate cases) exits are misclassified by our DGAPT tree.

**Table 9 Classification of New Exits under the DGAPT Model**

| Country | Time | Output Gap Change* | Depreciation** | Terminal Node | Performance |
|---|---|---|---|---|---|
| Argentina | 2002m2 | -3.6 | 258 | Orderly TN4 | Correct |
| Botswana | 2004m2 | na | -5 | Orderly TN4 | Indeterminate |
| Gambia | 2002m8 | -3.9 | 39 | Orderly TN4 | Correct |
| Kyrgyz Rep | 2003m1 | 6.7 | -5 | Disorderly TN5 | Incorrect |
| Moldova | 2002m11 | 9.2 | 4 | Orderly TN4 | Incorrect |
| Myanmar | 1983m5 | 4. 5 | 6 | Disorderly TN6 | Incorrect |
| Uganda | 2002m2 | 0.2 | 3 | Orderly TN4 | Correct |
| Uruguay | 2002m7 | -8.5 | 98 | Disorderly TN5 | Correct |
| Zimbabwe | 2003m3 | na | 1402 | Orderly TN4 | Indeterminate |
| **Memorandum Items:** | | | | | |
| **Orderly node's mean** | | -0.7 | 47 | | |
| **Disorderly nodes' mean** | | -9.5 | 82 | | |

*Output gap change between a year before and after exit.
**Depreciation rate between 6 months before and after exit.
Note: Mean, median, min. and max. values for cases found in TN4-TN7 are presented in Table 6.

Given the high misclassification costs, EXIT and DGAPT trees perform relatively well in placing new exit observations into the nodes they belong.

### IV.5.2 Robustness to Parameter Choice

As explained above, before running CART one has to decide on the option settings which range from *splitting criterion* to the *minimum size of the terminal nodes*. Clearly, by changing these options, we may get a different tree with a different size and structure. Each item in the option list has a different effect on the tree. For example, in the case of the minimum child node size, increasing it to, say, 5 from its default size of 1, would probably affect the size of the tree but not the selected splitters, especially in the upper parts of the tree. On the other hand, setting the missing penalty to 2 from the default of no penalty, would yield a completely different tree if the dataset includes missing observations. It is not possible to pin down the effects of changing options on the tree given the complex interactions they involve.

The table below shows the performance and the model information of the trees grown by changing **one option** of the EXIT tree in each step. The original options chosen to grow EXIT tree is given at the bottom of the table.

**Table 10 Parameter Check**

| Tree | Change | # of nodes | Relative Cost | Exit per node |
|---|---|---|---|---|
| 1 | *Standard Error Rule* set to **Within 1 SD of minimum** | 7 | 0.52 | 11.8 |
| 2 | *Splitting Criterion* set to **Gini** | 14 | 0.58 | 7.4 |
| 3 | *Splitting Criterion* set to **Twoing** | 14 | 0.58 | 7.4 |
| 4 | *Minimum child node size* set to **3** | 19 | 0.50 | 5.9 |
| 5 | *Missing penalty* set to **0** | 5 | 0.64 | 14.8 |
| 6 | *Missing penalty* set to **1** | 18 | 0.64 | 5.4 |
| 7 | *Missing penalty* set to **2** | 19 | 0.43 | 5.9 |
| **Memorandum Item** | | | | |
| EXIT | **Options Setting:** *Standard Error Rule* =**Minimum Cost Tree**; *Splitting Criterion* =**Entropy**; *Minimum Child node size*= **1**; *Missing Penalty*=**1.8** | 10 | 0.51 | 9.8 |

We find there is a trade-off between the cost and the size of tree; generally, the bigger the size (more nodes, more purity) the lower is the misclassification cost. However, as size grows, exit cases start to be represented in a single node which puts its representability under question. The last column of the table above shows the average number of exit cases within exit-prone nodes. Take for example *Tree 4*[20], which has a lower misclassification cost than EXIT tree. It has been grown with the same option setting except the *minimum child node size* which has been now set to **3**. The optimal tree has 19 nodes. Up to a certain level it is exactly the same as our EXIT tree but now TN1, TN2 and TN9 are split further into nodes. Why does this happen? Since the EXIT tree has child nodes with a minimum size of 13 (TN7), why do we end up with more nodes even if we set a higher limit for child node size? The answer is that this option affects the size at the level of maximal tree. If we look at the size of child nodes in the maximal tree of the EXIT model[21], we see that it has 6 nodes with only 1 observation. This is not the case in the maximal tree of *Tree 4,* in which the minimum number of observations is always higher than 2 (hence minimum child node size is 3). As expected, the maximal tree of *Tree 4* has 27 nodes compared to 31-node maximal tree of EXIT model. This option puts a limit on the tree size during the maximal tree growing phase of CART procedure. Once the maximal tree is found for *Tree 4*, testing phase sets in and tree has been pruned until the misclassification cost is minimized. And we reached the 19-noded *Tree 4*.

[20] *Tree 4* is presented in Figure A.III.5 in the Appendix.

[21] Maximal tree of EXIT Model is presented in Figure A.III.1 in the Appendix.

What are the differences between the EXIT tree and *Tree 4*? As mentioned above, cases in TN1, TN2 and TN9 have been split further. Let us take a closer look at the new nodes.

9 exit cases in TN2 of EXIT tree are now split under 3 new TNs following 3 new conditions. Burundi, Colombia, Guinea, Haiti, Iceland 00 and Kenya are separated from others by having a *peg duration* that is **longer than 159 months**. Dominican Republic is separated by having a *short-term to total debt ratio* that is **higher than 19.6%**, and finally, China and Iceland 75 are separated by exits that take place during periods when the *commodity price index* takes a value that is **higher than 138**.

Coming to the 12 exit cases in TN9 of EXIT tree, we see that node is split under 3 new TNs following 3 new conditions. Chile 82, Costa Rica, Czech Rep., Moldova, Paraguay, Slovak Rep. and Syria are separated from the others by having a *change in total external debt* that is **higher than 3%**. Malawi is separated by having a *budget balance* that is **smaller than -1.4%** and finally, Malaysia, Norway, Singapore and UK are separated by having *private credit* that is **higher than 63%** of GDP.

Note that these cases were once embedded in TN2 and TN9 of the EXIT tree. As mentioned before, surrogates can serve as a secondary source of information and if we check the surrogates for these nodes, we find that most of these new conditions have already been mentioned.[22]

## V. Parametric Methods and Comparison

The aim of this section is to compare CART results with those of obtained under regression framework (probit and Heckman selection model). CART trees split the sample into groups within which different vulnerabilities emerge and indicate threshold values beyond which these vulnerabilities become effective. The effects of the explanatory variables can be expected to be different under different groups, for example when the RER is overvalued and when it is not. Disregarding these differences, regressions run for the full sample may lead to incomplete and/or inconclusive results. Of course, the number of thresholds that can be accounted for depends on the sample size. With a bigger sample one can run separate regressions for each and every terminal node on the tree as long as the degrees of freedom permit this to be done. A smaller number of exits, unfortunately, does not allow for consideration of more than one threshold in this study. Therefore, we will only use the first threshold given by our EXIT tree, namely an RER overvaluation of 6.136%.

Recall that our EXIT tree started to split cases on the basis of overvaluation at the very top node. Cases with an overvalued RER (greater than 6.136%) go to the right and others to the left branch. All of the terminal nodes on the right branch are of the disorderly type. Overvaluation of the RER seems to be a very important factor.

Table 11 shows the probit estimation results where the binary EXIT variable is used as a dependent variable. After running the regression for the whole sample (note that among 650 observations, 224 of them have been dropped due to missing observations), we run the same model for the right (left) branch of our EXIT tree where overvaluation is greater (smaller) than 6.136%. The aim is to check how the

[22] See Table 3 and footnotes 9 and 11.

marginal effects of coefficients change once we restrict the sample to a smaller group of observations. Note that there are 85 (341) observations left after the exclusion of cases with lower (greater) overvaluation. The ratios of marginal effects of coefficients (evaluated at means) are given in the last 3 columns.

The changes in marginal effects of some variables are immense. Take for example, *forced* (speculative pressure dummy) which is found to increase the likelihood of exiting over the whole sample. But **its effect is multiplied (by more than 2 fold)** when *overvaluation of the RER* is present. And it is found to be insignificant when overvaluation is not an issue. The same is also true for the variable measuring *incidence of exit* in the preceding 12 months. Again, its effect is multiplied by more than 5 fold for countries having an overvalued RER. For the cases on the left branch where overvaluation is not present, this variable has a positive yet relatively small impact on exiting. The US interest rate which has been often used to account for push-pull sources of capital flows (see Calvo et al. 1996, Hausmann and Rojaz-Suarez 1996) is found to significantly increase the likelihood of exit, as expected. But surprisingly, once we restrict our sample to cases with an overvalued RER, contrary to our expectations, it loses significance albeit with a bigger marginal effect. As expected, it is less effective when there is no overvaluation.

**Table 11 Probit Estimates**

| | Full Sample (I) | Overvaluation >=6.136♣ (II) | Overvaluation <6.136♥ (III) | Marginal Effects Ratios | | |
|---|---|---|---|---|---|---|
| Variables | EXIT | EXIT | EXIT | II/I | III/I | III/II |
| ***Forced*** | 0.887 | 1.299 | 0.438 | 2.82 | 0.26 | 0.09 |
| | *(3.98)**** | *(2.85)**** | *-1.48* | | | |
| ***Output Gap*** | 0.097 | 0.012 | 0.099 | 0.36 | 0.61 | 1.70 |
| | *(3.72)**** | *-0.29* | *(3.14)**** | | | |
| ***Overvaluation*** | 0.036 | 0.106 | -0.011 | 8.18 | -0.18 | -0.02 |
| | *(3.07)**** | *(2.81)**** | *-0.57* | | | |
| ***Openness*** | -0.008 | -0.005 | -0.01 | 1.77 | 0.79 | 0.45 |
| | *(1.97)*** | *-0.69* | *(2.03)*** | | | |
| ***Exit Incidence*** | 6.675 | 12.128 | 7.697 | 5.02 | 0.68 | 0.14 |
| | *(3.53)**** | *(2.92)**** | *(3.13)**** | | | |
| ***Dep. Before*** | 0.015 | 0.017 | 0.011 | 3.03 | 0.46 | 0.15 |
| | *(2.22)*** | *-1.24* | *-1.23* | | | |
| ***Dom. Cr. to Prv. Sector*** | 0.002 | 0.023 | -0.006 | 25.82 | -1.37 | -0.05 |
| | *-0.65* | *(2.88)**** | *-0.8* | | | |
| ***Change in US interest rate*** | 0.549 | 0.296 | 0.602 | 14.91 | 0.65 | 0.04 |
| | *(1.87)** | *-0.52* | *(1.70)** | | | |
| **Observations** | 426 | 85 | 341 | | | |
| **Adjusted $R^2$** | 0.34 | 0.49 | 0.25 | | | |

Robust z statistics in parentheses. *significant at 10%; ** significant at 5%; *** significant at 1%; constant not reported. ♣Right branch of EXIT tree. ♥ Left branch of EXIT tree

*Domestic credit to private sector* has different impacts on exiting within the two subsamples. When overvaluation is present it significantly increases the likelihood of exiting, but in the absence of overvaluation its effect changes direction (the higher the credit smaller is the likelihood of exiting), although it becomes insignificant. This finding shows the importance of threshold effects. Note that within the full sample, the mean of domestic credit to the private sector is 46% of GDP; it is 41% for cases with overvaluation and 48% for cases without overvaluation. Overvaluation of the RER increases the vulnerability of countries to an increase in domestic credit. The same increase does not have the same effect in countries without an overvaluation problem.

As our EXIT tree portrayed, the *output gap* and *openness* are the most important splitters in the left branch of the tree where overvaluation is not present. This is also confirmed by our regression for the respective subsample (left branch). They are found to be significant in the regression run for the left branch observations but it is not the case for right branch observations.

Coming to the Heckman selection model estimates, results are given in Table 12.The same regression is run for the full sample and for the cases with and without overvaluation (equation 11).[23] Let us start with full sample results.

Facing speculative pressure, having a higher output gap, an overvalued RER, less openness, more incidence of exits, a less rigid pegged regime and a higher consumption gap above trend increases the likelihood of exiting (selection equations of regressions 1 and 7). Once these factors are accounted for, a higher output gap and longer duration of the peg significantly worsens the output deterioration following exit (main equations of regressions 1 and 3). Private investment, as opposed to private consumption, eases the exit by contributing positively to output growth. This shows the importance of the area into which credit expansion is channeled. All other things being equal, private consumption above trend decreases the output gap following exit (main equations of regressions 5 and 7).

As in the probit results, the *overvaluation threshold* has considerable effects on the Heckman results. In addition to changes in marginal effects (not reported here), some coefficients change their signs while others lose significance under different samples.

If we look at the main equations of regressions 3 and 4, and leaving other differences aside, *FDI to GDP* is found to be significant for the full sample but not in the sample where overvaluation is present. The budget balance is another variable whose effect differs when we take overvaluation into account. A higher *budget balance* decreases the *output gap change* following exit when overvaluation is present, while this is not significant for the full sample. The *duration* of pegging is significant and negatively contributes to exiting in an orderly way within the full sample, but its effect is nil on the right branch of the tree (main equation of 1-5, 7 and 9).

**Table 12** **Heckman Selection Model Estimates**

---

[23] Unfortunately, insufficient sample size and lack of independency of two equations (see Asici et al. 2007 for a discussion of statistical properties of Heckman selection models) limit the use of some subsample regressions presented in Table 11. As a result, discussion in the text depends on regressions number 1-5, 7, 9 and 10.

| Main Equation | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Change in Output Gap | All Sample | Right Branch♣ | All Sample | Right Branch | All Sample | Right Branch | All Sample | Right Branch | All Sample | Right Branch | Left Branch |
| Output Gap | -1.015*** | -1.070*** | -0.972*** | -1.044*** | -1.195*** | -0.726** | -0.799*** | -0.640** | -0.92*** | -1.04*** | -0.698*** |
| | [8.96] | [7.80] | [8.31] | [9.01] | [7.48] | [2.55] | [4.56] | [2.29] | [7.51] | [9.82] | [3.02] |
| Duration | -0.010* | 0.000 | -0.012* | 0.001 | -0.012* | -0.006 | -0.012* | -0.010 | -0.012** | -0.002 | -0.008 |
| | [1.65] | [0.02] | [1.85] | [0.18] | [1.96] | [0.72] | [1.77] | [1.11] | [2.03] | [0.31] | [0.76] |
| FDI | 0.430 | 0.023 | 0.577* | 0.677 | 0.120 | -0.160 | 0.230 | -0.123 | 0.58** | 1.05** | 0.334 |
| | [1.53] | [0.03] | [1.91] | [1.13] | [0.36] | [0.24] | [0.72] | [0.19] | [1.98] | [2.06] | [0.98] |
| Overvaluation | 0.048 | 0.015 | 0.026 | 0.023 | 0.016 | -0.015 | 0.018 | -0.007 | 0.031 | 0.045 | 0.161* |
| | [1.09] | [0.17] | [0.59] | [0.28] | [0.35] | [0.17] | [0.38] | [0.09] | [1.00] | [0.49] | [1.92] |
| Dom. Cr. To Prv. Sec. | -0.020 | -0.019 | -0.014 | -0.006 | | | | | | | |
| | [1.37] | [0.89] | [0.96] | [0.33] | | | | | | | |
| Budget Balance | | | 0.032 | -0.331** | | | | | -0.11 | -0.517*** | 0.143 |
| | | | [0.21] | [2.07] | | | | | [0.84] | [3.72] | [0.77] |
| Private Invest. Gap | | | | | 0.080* | -0.081 | | | | | |
| | | | | | [1.92] | [1.15] | | | | | |
| Private Cons. Gap | | | | | | | -0.279* | -0.417* | | | |
| | | | | | | | [1.87] | [1.81] | | | |
| Capital Control | | | | | | | | | 3.01** | 1.71 | 5.490** |
| | | | | | | | | | [2.56] | [1.62] | [2.10] |
| **Selection Equation Exit dummy** | | | | | | | | | | | |
| Forced | 0.738*** | 1.225*** | 0.829*** | 1.182** | 0.667*** | 1.364*** | 0.619** | 1.284*** | 0.849*** | 1.342*** | 0.481 |
| | [3.17] | [2.64] | [3.30] | [2.37] | [2.68] | [2.97] | [2.38] | [2.72] | [3.32] | [2.82] | [1.37] |
| Output Gap | 0.094*** | 0.016 | 0.118*** | 0.021 | 0.096*** | 0.034 | 0.024 | 0.024 | 0.125*** | 0.056 | 0.145*** |
| | [3.93] | [0.28] | [4.35] | [0.36] | [2.76] | [0.50] | [0.61] | [0.34] | [4.52] | [1.07] | [4.21] |
| Overvaluation | 0.036*** | 0.109*** | 0.031** | 0.098** | 0.040*** | 0.092** | 0.048*** | 0.095** | 0.031** | 0.079** | -0.011 |
| | [3.19] | [2.79] | [2.55] | [2.31] | [3.35] | [2.41] | [3.68] | [2.47] | [2.41] | [2.06] | [0.48] |
| Openness | -0.007** | -0.005 | -0.008** | -0.003 | -0.006 | 0.003 | -0.005 | 0.002 | -0.007* | 0.004 | -0.013** |
| | [2.08] | [0.60] | [2.19] | [0.30] | [1.59] | [0.47] | [1.33] | [0.31] | [1.77] | [0.60] | [2.09] |
| Incidence of Exits | 4.884** | 11.151** | 5.255** | 11.102** | 5.309** | 9.846** | 5.452** | 10.313** | 5.119** | 7.933* | 5.585 |
| | [2.17] | [2.42] | [2.20] | [2.22] | [2.25] | [2.15] | [2.21] | [2.24] | [2.07] | [1.79] | [1.60] |
| Regime Flexibility | 0.020*** | 0.018 | 0.020*** | 0.019 | 0.024*** | 0.021 | 0.025*** | 0.020 | 0.019*** | 0.011 | 0.020** |
| | [3.18] | [1.17] | [3.09] | [1.14] | [3.29] | [1.40] | [3.17] | [1.35] | [2.95] | [0.78] | [2.41] |
| Dom. Cr. To Prv. Sec. | 0.002 | 0.022*** | 0.004 | 0.025*** | | | | | | | |
| | [0.77] | [2.65] | [1.24] | [2.71] | | | | | | | |
| Budget Balance | | | 0.039 | 0.027 | | | | | 0.043 | 0.049 | 0.032 |
| | | | [1.49] | [0.48] | | | | | [1.59] | [0.94] | [0.89] |
| Private Invest. Gap | | | | | -0.005 | 0.002 | | | | | |
| | | | | | [0.53] | [0.09] | | | | | |
| Private Cons. Gap | | | | | | | 0.068** | 0.025 | | | |
| | | | | | | | [2.25] | [0.47] | | | |
| Capital Control | | | | | | | | | 0.054 | -0.460 | 0.416 |
| | | | | | | | | | [0.19] | [0.88] | [0.99] |
| Observations | 428 | 86 | 396 | 80 | 399 | 78 | 391 | 77 | 369 | 76 | 292 |
| Uncensored obs. | 376 | 58 | 348 | 55 | 352 | 53 | 345 | 51 | 324 | 53 | 271 |
| Censored Obs. | 52 | 28 | 48 | 25 | 47 | 25 | 46 | 26 | 45 | 24 | 21 |
| Wald Chi² | 121.3 | 92.1 | 107.6 | 114.3 | 108.8 | 70.3 | 128.5 | 98.2 | 126.5 | 150.1 | 71.48 |
| Rho | 0.56 | 0.85 | 0.58 | 1 | 0.53 | 0.49 | 0.47 | 0.22 | 0.47 | 0.94 | 0.339 |
| Mill's Ratio | 2.070** | 2.798** | 2.080** | 2.811*** | 1.935** | 1.554 | 1.673* | 0.673 | 1.529* | 2.15** | 0.963 |
| | [2.28] | [2.36] | [2.33] | [2.88] | [2.19] | [1.23] | [1.82] | [0.48] | [1.79] | [2.39] | [0.72] |

Absolute value of z statistics in brackets. * significant at 10%; ** significant at 5%; *** significant at 1%

♣ Right (Left) Branch of EXIT tree contains observations with overvaluation greater (smaller) than 6.136%.

Coming to the role capital controls play during exit, the results confirm the conclusion reached in Asici et al. (2007) that capital controls ease the pain during exiting by significantly contributing to the output gap. But its effect becomes insignificant when we limit our analysis to the right branch where overvaluation is present (main equations of regressions 9 and 10).

These exercises show the importance of threshold effects (non-linearities) in analyzing events where combined effects of fragilities together are responsible in the making of events like exiting, crises etc. They also show that the conventional strength of parametric methods can be dramatically improved by employing the non-parametric CART methodology. This can be seen from the changes in coefficient estimates in terms of both magnitude and sign, when the full sample is split in line with the thresholds given by CART. Note that the sample size prevented us from accounting for more than 1 threshold. With a larger sample size one can further refine the results by running the same regressions for smaller groups of countries, i.e. for each terminal node at the limit. Under regression framework, it is theoretically possible to compute marginal effects at some values other than sample means. However, practically these exact values are unknown to a researcher. CART analysis shows where to look, how and at what value non-linearities emerge. In short, it would not be wrong to claim that both approaches are complementary to each other rather than substitutes.

## VI. Conclusions

IMF's *de facto* regime classification reveals that among 187 countries, 111 of them have been pursuing one form of fixed regime (ranging from currency board to crawling peg) as of August 2006. Out of the 132 countries covered in this paper, the Harvey et al. (2005) dataset reveals that 65 countries were still expected to take steps towards liberalization as of end-2005. When and how to exit is still an important question, given the fact that the most disruptive exits have occurred during the post-liberalization period. The challenges confronting developing countries with fixed regimes are obvious.

Overvaluation of the RER, a higher output gap above trend coupled with a private consumption boom and speculative pressure before exit are the most important factors lying behind disorderly exits. Ill-managed financial liberalization and macroeconomic stabilization programs sow the seeds of fragilities that eventually lead countries to abandon their pegs in the midst of a crisis. Moreover, negative terms of trade shocks and a rapid increase in external debt a year before exit increase the likelihood of exiting in a disorderly fashion, especially when the RER is overvalued. Having a less rigid fixed regime may limit overvaluation of the RER but it is not enough to save countries from exiting in a disorderly fashion. Our EXIT tree revealed that in the absence of overvaluation, the output gap is the most important condition separating disorderly exits from orderly ones. A closer look at countries hints that countries with more rigid fixed regime have done relatively better in keeping their output on trend following exit.

For the majority of disorderly exits, close comovement of private credit with consumption, investment and output before exit is clearly observed. This continues to hold following the exit but in the opposite direction. As credit lines dry up, consumption and investment fall, leading output to collapse. One interesting point is that it is not rapid credit growth per se that is important but the activity into which credit has been channeled, i.e. consumption or investment. If credit is used to finance private consumption, this makes exits more painful as our regression results showed. In contrast, credit expansion which is used to finance private investment helps countries sustain their output growth on-trend, everything else being equal. Our DGAPT tree shows that this conclusion holds, however, only when there is no contemporaneous consumption and investment boom. A private investment boom, if coupled with a consumption boom, is associated with more painful exits.

Our analysis also shows the importance of the timing of financial liberalization. Almost all countries placed in orderly nodes exited before liberalization. And all of them have capital controls in place. We did not detect any major deviation of the RER nor of the output gap from their long-term trend in the magnitudes of disorderly exits experienced. The increased financing opportunities following liberalization, if not adequately monitored, carry the potential of creating unsustainable economic boom and pave the way to an eventual bust period. Therefore, without loss of generality we can conclude that, countries would do better by instituting exchange rate flexibility before taking liberalization steps.

Inadequately managed financial liberalization is not the only source of volatility however. Stabilization programs have also been critiqued for creating boom-bust cycles in domestic economies. Irrespective of liberalization almost all the countries in our sample, whose stabilization episodes ended by exiting the peg, have done so in a disorderly fashion. Countries should keep in mind that poorly-constructed stabilization plans may become a source of bigger instability in the future.

We nowadays observe fewer occurrence of financial crisis, as compared to the 1990s. This can be attributed to two developments: the first one is the favorable external conditions, namely the lax monetary stance in world financial centers and high commodity prices. Both developments are helping developing countries sustain high levels of growth. Secondly, especially after the Asian crises, international financial institutions put more emphasis on the health and regulation of the domestic financial sector. Prudent banking standards and regulation help countries cope with the negative consequences of capital outflows. Favorable external conditions should not be expected to continue forever, however. The current path of strong growth can be sustained in the long-run by taking steps to lessen sources of vulnerabilities while markets are calm. As mentioned, adequate regulation and supervision of financial sector is one of these. The existence of shocks, like terms of trade collapse, constitutes another source of vulnerability. In this respect, countries should be encouraged to diversify their production mix beyond primary products so as to contain the disastrous effects of price slumps in world markets.

Coming to the comparison of two approaches, we see that conventional strengths of parametric methods can be dramatically enhanced by non-parametric methods, especially when analyzing discontinuous events like crises and exiting from pegs . A standard regression framework is not wholly appropriate to measure the combined effects of variables. Disregarding the existence of non-linearities may lead to dismissal of important variables from the analysis and lead to wrong or incomplete conclusions. Non-parametric methods are useful at uncovering these kinds of non-linearities and can guide researchers where to look and more importantly indicate threshold values beyond which they become effective. In that sense two approaches should not be seen as substitutes but as complements.

## a. References


Agénor, Pierre-Richard (2004) "Orderly Exits from Adjustable Pegs and Exchange Rate Bands", *Journal of Economic Policy Reform*, Vol. 7, Issue 2, pp: 83-108.

Aghion, Phillippe, Philippe Bacchetta and Abhijit Banerjee (2004), ''The Financial Development and the Instability of Open Economies'', *Journal of Monetary Economics* 51 (2004), No. 6, pp. 1077-1106.

Aizenman Joshua and Reuven Glick (2006) "Pegged Exchange Rate Regimes –A Trap?", NBER Working Paper 11652.

Aşıcı, Ahmet Atıl (2002) "On Crisis-Driven and Peaceful Exit from Peg to More Flexible Arrangements: Factors Behind Successful Exits", Master Thesis, Graduate Institute of International Studies, Geneva, October.

Aşıcı, Ahmet Atıl and Charles Wyplosz (2003) "The Art of Gracefully Exiting a Peg", *The Economic and Social Review*, 34(3): 211-28.

Aşıcı, Ahmet Atıl, Nadezhda Ivanova and Charles Wyplosz (2007) "How to Exit from Fixed Exchange Rate Regimes", forthcoming in *International Journal of Finance and Economics*

Bekeart, Geert, Campbell R. Harvey and Christian Lundblad (2005), ''Does Financial Liberalization Spur Growth?'', *Journal of Financial Economics*, 77, 3-55.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999) ''The Financial Accelerator in a Quantitative Business Cycle Framework.'' In *Handbook of Macroeconomics,* ed. by John B. Taylor and Michael Woodford, 1341–90. Amsterdam:North-Holland.

Bubula, Andrea and Inci Otker-Robe (2002) "The Evolution of Exchange Rate Regimes Since 1990: Evidence from De Facto Policies", IMF Working Paper WP/02/155.

Calvo, Guillermo, Leonardo Leiderman and Carmen Reinhart (1996) "Inflows of Capital to Developing Countries in the 1990s" , *Journal of Economic Perspectives* 10(2), Spring, pp. 123-39.

Calvo, Guillermo and Carlos Vegh (1999) "Inflation Stabilization and BOP Crises in Developing Countries" Handbook of Macroeconomics, ed. by John Taylor and Micheal Woodford (Chicago: University of Chicago Press)

Chang, Roberto and Andres Velasco (2000) "Financial Fragility and the Exchange Rate Regime", *Journal of Economic Theory* 92(1): 1-34.

Demirguc-Kunt, Asli and Enrica Detragiache (1998), "Financial Liberalization and Financial Fragility", World Bank Policy Research Working Paper series No. 1917

Detragiache, Enrica, Ashoka Mody and Eisuke Okada (2005) "Exits from Heavily Managed Exchange Rate Regimes", IMF Working Paper "P/05/39.

Duttagupta and Inci Otker-Robe (2003) "Exits from Pegged Regimes: An Empirical Analysis", IMF Working Paper WP/03/147.

Edwards, Sebastian and Igal Magendzo (2003) "A Currency of One's Own? An Empirical Investigation on Dollarization and Independent Currency Unions", NBER Working Paper No. 9514.

Eichengreen, Barry and Paul Masson (1998) "Exit Strategies: Policy Options for Countries Seeking Greater Exchange Rate Flexibility", *IMF Occasional Paper* 168.

Eichengreen, Barry and Raul Razo-Garcia (2006) "The International Monetary System in the Last and Next 20 Years", *Economic Policy* Vol.21, Issue 47:393-442.

Fischer, Stanley (2001) "Exchange Rate Regimes: Is the Bipolar View Correct?", *Journal of Economic Perspectives* 15(2): 3-24.

Genberg, Hans and Alexander Swoboda (2005) "Exchange-Rate Regimes: Does What Countries Say Matter?", *IMF Staff Papers*, Vol. 52, special issue, Washington D.C.

Ghosh, Swati R. and Atish R. Ghosh (2003) "Structural Vulnerabilities and Currency Crises", *IMF Staff Papers*, Vol. 50, No: 3, Washington D.C.

Ghosh, Atish, Anne-Marie Gulde, and Holger C. Wolf (2003) *Exchange Rate Regime: Choices and Consequences*, Cambridge: MIT Press.

Gourinchas, Pierre-Olivier, Rodrigo Valdes and Oscar Landerretche (2001), "Lending Booms: Latin America and the World", *Economia*, Vol.1 (Spring), pp. 47-99

Hamann, A. Javier, Andres Arias and Lei Zhang (2005) "Monetary and Exchange Rate Dynamics during Disinflation: An Empirical Analysis", IMF WP/05/33, Washington D.C.

Hausmann, Ricardo and Liliana Rojas-Suarez (eds) (1996) *Volatile Capital Flows: Taming their Impact on Latin America*, Baltimore: Johns Hopkins University Press.

Heckman, James J. (1979) "Sample Selection Bias as a Specification Error", *Econometrica* 47:153–161.

Kaminsky, Graciela (2003) "Varieties of Currency Crises" NBER Working Paper No. 10193.

Kaminsky, Graciela and Sergio Schmuckler (2002), "Short-Run Pain, Long-Run Gain: The Effects of Financial Liberalization", Policy Research Working Paper Series, No: 2912, World Bank, Washington D.C.

Klein, Michael and Nancy Marion (1997) "Explaining the Duration of Exchange Rate Pegs", *Journal of Development Economics* 54(2): 387-404.

Levine, Ross (1997), "Financial Development and Growth: Views and Agenda", *Journal of Economic Literature*, Vol. 35 (June), pp. 688-726

Levy-Yeyati, Eduardo, Federico Sturzenegger and Iliana Reggio (2006) "On the Endogeneity of Exchange Rate Regimes", KSG Working Paper No. RWP06-047.

Manasse, Paolo, Nouriel Roubini and Axel Schimmelpfennig (2003) "Predicting Sovereign Debt Crises", IMF WP/03/221 Washington D.C.

Masson, Paul and Francisco Ruge-Murcia (2005) "Explaining the Transition between Exchange Rate Regimes", *Scandinavian Journal of Economics*, Vol. 107(2), pp: 261-278, 06.

Mundell, Robert A. (1961), "A Theory of Optimum Currency Areas", *American Economic Review*, 51, November, pp. 509-17.

Ranciere, Romain, Aaron Tornell and Frank Westermann (2005) "Systemic Crises and Growth", NBER Working Paper No. 11076.

Rebelo, Sergio and Carlos Végh (2006) "When Is It Optimal to Abandon a Fixed Exchange Rate?", NBER Working Paper No. 12793.

Reinhart, Carmen and Kenneth Rogoff (2004) “The Modern History of Exchange Rate Arrangements: A Reinterpretation”, *Quarterly Journal of Economics* 119 (1): 1-48.

Tornell, Aaron and Frank Westermann (2002) "Boom-Bust Cycles: Facts and Explanation", NBER Working Paper No. 9219.

Wyplosz, Charles (2002), “How Risky is Financial Liberalization in the Developing Countries?”, *Comparative Economic Studies* 44(2-3): 1-26.

## Appendices

### Appendix 1. Speculative Pressure Index (SPI)

In the literature the SPI is widely used to capture speculative attacks, often to pin down crisis date. However, with small modifications it can equally be used as an early-warning device. For example, a small increase in the interest rate may be enough to put the debt dynamics into an unsustainable path and lead the country to a crisis. Standard SPI can possibly detect the final attack whose seeds have been sowed earlier. Our aim is to capture these small pressures which carry the potential to trigger a full-scale attack. Using the earthquake analogy, the device should not only deal with the amplitute of tsunami waves on the coast, but should also be sensitive to the occurrence of small waves at the epicentre of the earthquake. Since it is this small waves becoming the destructive tsunami vawes eventually on the coast.

After two modifications over the standard SPI one can reach such a device. By, decreasing the threshold beyond which the SPI signal attack, and secondly by lengthening the period over which speculative pressure is monitored.

The details concerning these two modifications will be explained below, but before let us mention some general considerations in the SPI construction.

- SPI should include the changes in exchange rate, the changes in international reserves and the changes in relevant interest rate, if available. The inclusion of latter is critical, however many studies fail to include it on the grounds that not many developing countries have data on interest rate. But the fact that many countries do not have it should not lead to ruling out this component from the index immediately. There are developing countries with the relevant rate and as our observations showed this information can change results dramatically and therefore should not be disregarded. Hence, the index should be calculated with the interest rate component for developing countries having a relevant rate. A preliminary look at the data verified that there are many instances where the index without interest rates fails to detect a speculative attack when there is actually one. Take, for example Ecuador's March 1999 exit, it was precipitated by a speculative pressure captured mainly by the increase in the **discount rate** although the index computed by the exchange rate and the reserve changes alone did not signal any pressure.
- Hyper-inflationary periods are often characterized by high rate of currency depreciation and high interest rate changes. Computing a single index with hyper and normal inflation cases together may bias the results. Therefore these cases have to be dealt separately. The threshold which divides hyperinflation and normal inflation countries is chosen as 150% measured as the average of last 6 months.
- Which interest rate is the relevant one is also an important question: the discount rate, the t-bill rate or the money market rate? A closer look at the data shows that different countries seemed to use different interest rates to defend their currency. For example, it is the **money market rate** which has been used to defend the currency, not the discount or the t-bill Rate during Turkey's February 2001 exit. Or, Canada in January 1997 and France in July 1987 used the **t-bill** rate as they defended their currency.

- Therefore, speculative pressure should be searched by computing several indices with different interest rates.

To avoid imposing any group of countries' experience to others, we calculated all indices with *discount rate, money market rate* and *t-bill rate* separately.

For each subgroups (normal inflation, hyperinflation) we calculated 4 indices, which are formulated as follows:

$S_{1t} = (e_t/\sigma_e) - (r_t/\sigma_r)$

$S_{2t} = (e_t/\sigma_e) - (r_t/\sigma_r) + (d_t/\sigma_d)$

$S_{3t} = (e_t/\sigma_e) - (r_t/\sigma_r) + (m_t/\sigma_m)$

$S_{4t} = (e_t/\sigma_e) - (r_t/\sigma_r) + (t_t/\sigma_{tbill})$

where $e_t$ stands for depreciation of blackmarket exchange rate, $r_t$ for percentage change of international reserves excluding gold and $d_t$ , $m_t$ and $t_t$ for monthly changes in discount rate, money market rate, and t-bill rate, respectively.

The next step is to define a threshold and identify months with speculative pressure. For each indices, *mean+1*standard deviation* threshold is used, months with higher values take a value of 1, and 0 otherwise. This threshold may seem to be lower. In the currency crises literature, normally, mean over three standard deviation is used as a threshold. But such a high threshold is too stringent for our purposes here. Our aim is not to identify crises month, but just to see whether countries face difficulties or not in their foreign exchange market in the year to exit. In other words, we prefer to use this index as a sender of early warning signal, not only as a bell marking the end, like identifying the date of currency crash.

Then the SPI index is calculated as

$SPI_{it}$=1 if $S_{it} > \mu_{Si} + 1 * \sigma_{Si}$, 0 otherwise,

with μ being mean and σ as standard deviation, and $i=1,2,3$ and $4$.

After identifying months with speculative for each indices, a combined index is created by following the rules below.

$SPI_t = S_{1t}$ if none of the 3 interest rate is available, and

$SPI_t = max\ \{S_{2t}, S_{3t}, S_{4t}\}$ otherwise.

An exit (also no-exit), then, is deemed to be preceded by a *forced* period if this combined index takes a value of 1 during the previous 12 months preceding exit and no-exit dates.

After computing the index above we see that, in our original dataset, out of 566 observations 83 (32 exit and 51 no-exit cases) of them experienced a period of speculative pressure (forced equals to 1).[24]

Why not taking the value a month before exit instead of monitoring previous 12 months? The reason is that speculative pressure may have long-lasting effects. The higher the maturity and currency mismatches of

[24] As a sensitivity check, if one uses *mean plus two standard deviation* as a threshold, this number falls to 18 with 12 of them belonging to exit and 6 to no-exit cases. Or else, keeping the threshold as same but *shortening the monitoring period from 12 months to 6 months before exiting* left us with 60 cases, 30 exit and 30 no-exit cases. As a result, index is quite sensitive to threshold selection but not to period selection.

financial sector, the higher is the damage of a unit increase in interest rates and devaluation of nominal exchange rate on financial balances, respectively. Apart from its detrimental effect on financial sector balances, a speculative attack may also raises doubts over the sustainability of sovereign debt by increasing the interest rate governments have to offer to roll their debts (or by increasing debt service in local currency). To address these concerns, therefore, we chose to monitor speculative pressure throughout the year, rather than a month before exit. Another point we want to make is about labeling no-exit cases as *forced* or *unforced*. As our analysis shows there are 51 cases in our no-exit sample (12%) where countries continued to peg despite the speculative pressure they faced. Since our analysis deals with exit and no-exit cases jointly, this additional information on no-exit cases would provide a perspective to the role speculative pressure plays during exits.

**Appendix 2. CART Methodology**

**I. CART Algorithm**

The algorithm involves two opposing segments. A *purity-greedy* segment tends to grow the tree with a maximum number of nodes (as many as the number of observations, as long as purity increases by splitting). A *generality-greedy* segment on the other hand operates in exactly the opposite manner, by getting rid of individual-observation-specific rules that can not be generalized, hence favoring smaller trees. The battle between these two opposing segments yields the tree within which purity and generality are optimized. It is called the optimal tree and by construction it will be robust when applied to completely new datasets.

CART starts by examining all possible splits and then it ranks order each splitting rule. The rule which makes the highest improvement (highest decrease in heterogeneity within left and right child nodes) is chosen as a primary splitter. The splitting process continues until it is impossible to do so. At the end of this recursive process we reach to the maximal tree. The next segment of the algorithm, testing phase, kicks in at this point. Once the maximal tree is reached, CART starts to cut back the tree and prepares a set of sub-trees with different number of nodes. Then these sub-trees are taken to a testing procedure. The testing procedure evaluates the performance of each sub-tree under different subsamples. Generally (when dataset is small, that is having less than 3000 observations), subsamples are generated through random sampling of the original dataset and the sub-tree with the least misclassification cost is chosen as an optimal tree.

Now let us follow the steps of testing phase when applied to our EXIT model.

1) *Maximal Tree Growing*: When we run CART on our dataset with 566 cases (59 exits and 507 no-exits), CART grew a maximal tree with 31 nodes as presented below. This is the maximum size tree given the stopping rules as mentioned before. By cutting branches sequentially CART forms 16 different sub-trees with different number of nodes ranging from 1 (no split case) to 31 nodes. Of course, the tree with the highest number of nodes (tree number 1 with 31 nodes) has the least misclassification cost of 0.047 under the full sample. On this maximal tree 24 no-exit cases have been placed into exit prone nodes (nodes with a conditional probability of exit exceeding 10%, the unconditional probability at the top node). All exit cases have been correctly placed into one of exit prone nodes. Misclassification cost over the full sample (called formally as Resubstitution Relative Cost in CART jargon) is then found as 0.047 by adding misclassification rates of each class (24/507+0/59=0.047).

2) *Pruning:* As mentioned before, the maximal tree is not optimal unless it has been verified by the testing procedure. Testing procedure produces 10 maximal trees with different portions of original sample in each cross-validation step (90% of original dataset). The remaining 10% of the samle is reserved for testing. Since the original dataset is partitioned into 10 equal parts, CART grows 10 maximal trees, with 509 (90% of 566) cases of which 53 of them are exit and 456 no-exit cases. Accordingly, *testing sample* contains 57 cases (10% of 566), 6 of them are exit and 51 no-exit

cases. Note that proportion of exit cases in each sample reflects the original proportion in the original dataset where exit cases account for 10.4% of observations.

The maximal trees grown in each CV steps are listed as follows:

CV Tree 1: 26 Nodes

CV Tree 2: 28 Nodes

CV Tree 3: 26 Nodes

CV Tree 4: 27 Nodes

CV Tree 5: 31 Nodes

CV Tree 6: 26 Nodes

CV Tree 7: 28 Nodes

CV Tree 8: 27 Nodes

CV Tree 9: 25 Nodes

CV Tree 10: 29 Nodes

Each of the CV trees above, by construction, consists of similar branches (sub-trees), some with long branches and some with short (for example compare CV Tree 5 with 31 nodes and CV Tree 4 with 27 nodes; upto a certain depth these two trees have similar splits, then CV Tree 4 was stopped but CV Tree 5 was continued to grow until it reached 31 nodes).

All CV trees have sub-trees with 1, 2, 15, 20 nodes etc. and they contain the same splits. Clearly one should expect to see the similar splits in relatively close position of each tree since, what is important within the full sample (as a splitter) would probably be important within these subsamples (90% of the original sample) as well.

3) *Testing:* Now that we have *ten* 1-node trees, *ten* 2-node trees etc. And in the coming step each of these tree groups will be tested *ten* times with the remaining 1/10 of the sample. After horse-racing different tree groups (1-noded, 2-noded etc.), the sub-tree with the *least misclassification error rate* is chosen as an *optimal* tree. The relative cost is again measured as a ratio of misclassified cases in total and it is fair to expect that each subsample test would yield different but close ratios. That is why in the report, relative cost ratio is given within a confidence interval (mean plus/minus standard deviation of ratio).

**Tree Sequence**

| Tree Number | # of TNs | Cross-Validated Relative Cost | Resubstitution Relative Cost | Complexity |
|---|---|---|---|---|
| 1 | 31 | **0.692 +/- 0.065** | **0.047** | 0.000000 |
| 7 | 21 | 0.530 +/- 0.065 | 0.114 | 0.005434 |
| 8 | 19 | 0.518 +/- 0.064 | 0.142 | 0.007005 |
| 9 | 15 | 0.533 +/- 0.065 | 0.210 | 0.008485 |
| 10 | 12 | 0.524 +/- 0.065 | 0.266 | 0.009348 |
| 11 | 11 | 0.526 +/- 0.065 | 0.286 | 0.009872 |
| **12*** | **10*** | **0.512 +/- 0.064** | **0.306** | **0.010089** |
| 13 | 7 | 0.520 +/- 0.064 | 0.372 | 0.010970 |

| Tree Number | # of TNs | Cross-Validated Relative Cost | Resubstitution Relative Cost | Complexity |
|---|---|---|---|---|
| 14 | 3 | 0.674 +/- 0.067 | 0.467 | 0.011844 |
| 15 | 2 | 0.710 +/- 0.067 | 0.594 | 0.063828 |
| 16 | 1 | 1.000 +/- 0.000 | 1.000 | 0.202932 |

* Minimum Cost
** Optimal

As seen from the table above, the 12th tree with 10 nodes is chosen as an optimal tree with the least "cross validated (CV) relative cost ratio" (0.512-/+0.064). Should there be no testing one would choose 1st tree with least relative cost ratio that is 0.047. But testing with 10 different subsamples shows that 1st tree with 31 nodes do not perform well in placing cases into right nodes as compared to the 12th tree, which can be seen from the CV relative cost figures above (0.512 vs. 0.692).

The testing procedure shows that the optimal tree with 10 nodes has the *least CV relative cost* of 0.512 (decomposed as 0.16 from no-exit cases and 0.36 from exit cases).

**Misclassification for Test Data**

| Class | N Cases | N Mis-Classed | Pct Error | Cost |
|---|---|---|---|---|
| 0 | 507 | 79 | 15.58 | 0.16 |
| 1 | 59 | 21 | 35.59 | 0.36 |

The figures above reflect the misclassification rate under test data. Since in each testing step different 1/10th part of data is used, and after 10 tests, we reach the total number of observation which is 566. Note that optimal tree selection is made depending on these figures, not full sample cost.

Once we determine the optimal number of nodes, CART picks and presents this specific tree from the pool of trees it created in the first phase. Since it has been grown by the full sample, the misclassification rate is 20% lower than its counterpart under testing sample (compare costs under full and test samples for 10-noded tree, 30.6% vs. 51.2% respectively). Under the full sample, misclassification of exit cases accounts for only 3%. That is, in our EXIT tree 2 exit cases have been placed in no-exit prone nodes and these observations are Japan 1977, Poland 2000 in TN1.

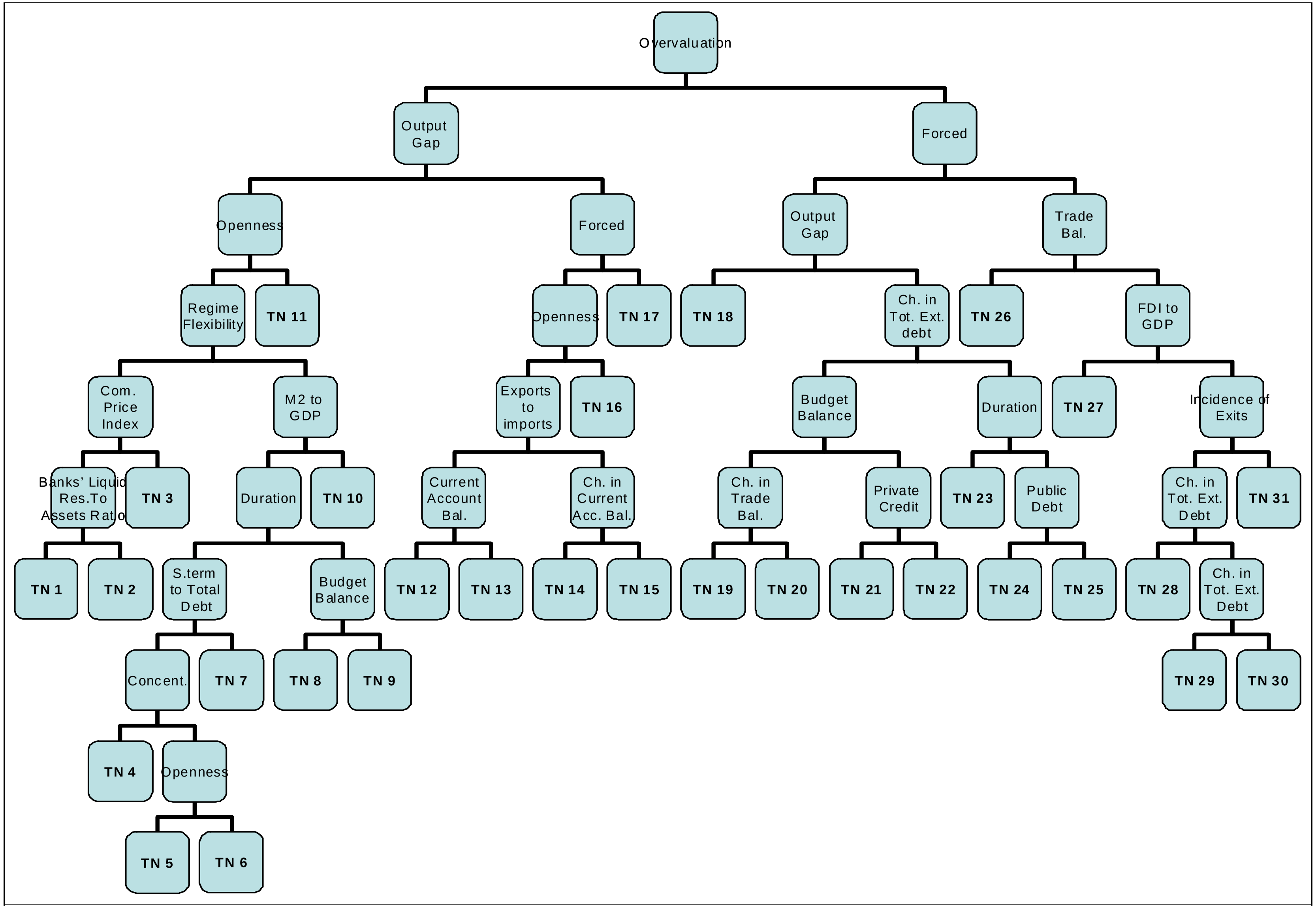
**Misclassification for Learn Data (Full Sample)**

| Class | N Cases | N Mis-Classed | Pct Error | Cost |
|---|---|---|---|---|
| 0 | 507 | 138 | 27.22 | 0.27 |
| 1 | 59 | 2 | 3.39 | 0.03 |

## II. Surrogates

Depending on the splitter criterion, CART chooses a splitter having the highest improvement score, possibly adjusted by missingness. For each splitter CART automatically computes a set of splitters called as "surrogates", which contain information that is typically similar to what would be found in the primary splitter. In other words, a surrogate is a splitter that closely mimics the action of the primary splitter. In our EXIT tree analysis we found that overvaluation is the most powerful splitter. That is, overvaluation makes the biggest improvement in splitting exit cases from no-exit cases. But there are cases for which overvaluation data is missing. Here the surrogate splitters come into scene. Rather than dropping these cases immediately, CART continues to keep them and split them to right or left depending on the information given by surrogates. Of course, surrogate's performance, which is measured by a statistics called as "association", differs in mimicking primary splitter. If a surrogate splits observations exactly in the same way as primary splitter does, then association value takes its maximum value 1, indicating that both variables can be used interchangeably. Therefore, depending on their association value, surrogates provide a secondary source of information.

**Figure A.III.1** **Maximal Tree of EXIT Model**



**Appendix 3. Sample and Data**

**Table A.III.1 Exit Observations**

| | | |
|---|---|---|
| **Algeria (1988m1)** | **Iceland (1975m8, 2000m10)** | **Nicaragua (1979m4)** |
| **Argentina (1981m3,** 2002m2) | **Indonesia (1997m8)** | **Norway (1982m8, 1992m12)** |
| **Australia (1982m8)** | **Iran (1978m11)** | **Paraguay (1981m9,** 2000m12) |
| Botswana (2004m2) | **Iraq (1981m1)** | **Philippines (1983m10, 1997m7)** |
| **Brazil (1999m2)** | **Italy (1976m1)** | **Poland (2000m4)** |
| **Burundi (1996m5)** | **Japan (1977m2)** | **Russian Federation (1998m9)** |
| **Chile (1982m6, 1999m9)** | **Kenya (1987m1)** | **Singapore (1997m7)** |
| **China (1981m3)** | **Korea (1997m12)** | **Slovak Republic (1998m10)** |
| **Colombia (1983m5, 1999m10)** | Kyrgyz Republic (2003m1) | **Suriname (1982m5)** |
| **Congo, Dem. Rep. (1975m1)** | **Lebanon (1984m3)** | **Sweeden (1992m12)** |
| **Costa Rica (1980m10)** | Liberia (2000m12) | **Syria (1982m6)** |
| **Czech Republic (1997m6)** | **Madagascar (1987m6)** | **Thailand (1997m7)** |
| **Dominican Rep. (1982m9)** | **Malawi (1997m7)** | **Turkey (1980m1, 2001m2)** |
| **Ecuador (1982m3, 1999m2)** | **Malaysia (1997m8)** | **United Kingdom (1992m9)** |
| **El Salvador (1985m9)** | **Mexico (1982m2, 1995m1)** | Uganda (2002m2) |
| Gambia (2002m8) | **Moldova (1998m8)** | **Uruguay (1982m12,** 2002m7) |
| **Greece (1981m7)** | **Myanmar (1983m5)** | **Venezuela (1983m3)** |
| **Guinea (1999m11)** | **New Zealand (1985m3)** | **Zimbabwe (1983m7,** 2003m3) |
| **Haiti (1993m5)** | | |

Source: Reinhart Rogoff (2004) and Eichengreen and Razo-Garcia (2006) datasets.
Note: The date is the month of exit. Cases used in tree analysis are highlighted in bold, other cases have been included in the sample which is used in robustness checks.

**Table A.III.2 No-Exit Observations**

| | | |
|---|---|---|
| Algeria (1976, 1979,1982,1985,1997,2000) | Honduras (1976,1979,1982,1985,1988, 1993,1996, 1999, 2002) | Morocco (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Argentina (1981, 1993, 1996, 1999, 2002) | Hong Kong (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Nepal (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Armenia (1997, 2000, 2003) | Hungary (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Netherlands (1976,1979,1982,1985,1988, 1991,1994, 1997) |
| Australia (1976, 1979) | Iceland (1985, 1988, 1991, 1994, 1997) | New Zealand (1976,1979,1982) |
| Austria (1976,1979,1982,1985,1988, 1991,1994, 1997) | India (1976,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Nicaragua (1976, 1994, 1997, 2000, 2003) |
| Azerbaijan (1998, 2001, 2004) | Indonesia (1976,1979,1982,1985,1988, 1991,1994) | Norway (1976,1979,1989) |
| Belgium (1979,1982,1985,1988, 1991,1994, 1997) | Iran (1975) | Pakistan (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Bolivia (1989, 1992,1995, 1998, 2001, 2004) | Iraq (1975, 1978) | Panama (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Bosnia-Herzegovina (1996, 1999, 2002) | Ireland (1976,1979,1982,1985,1988, 1991,1994, 1997) | Paraguay (1975, 1978, 1988, 1991, 1994, 1997, 2000) |
| Botswana (1977,1980,1983,1986,1989, 1992,1995, 1998, 2001, 2004) | Israel (1988, 1991,1994, 1997, 2000, 2003) | Peru (1995, 1998, 2001) |
| Bulgaria (1999, 2002) | Italy (1985,1988, 1991,1995, 1998) | Philippines (1977,1980, 1988, 1991, 1994) |
| Burundi (1975,1978, 1981, 1984, 1987, 1990, 1993, 1999) | Jamaica (1976,1981,1984,1987,1995, 1998, 2001, 2004) | Poland (1997) |
| Canada (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Jordan (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000) | Portugal (1976,1979,1982,1985,1988, 1991,1994, 1997) |
| Chile (1979, 1990, 1993, 1996) | Kazakhstan (1998, 2001, 2004) | Romania (2003) |
| China (1978, 1994, 1997, 2000, 2003) | Kenya (1981, 1984) | San Marino (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000) |
| Colombia (1977, 1980, 1987, 1990, 1993, 1996) | Korea (1976,1979,1982,1985,1988, 1991,1994) | Saudi Arabia (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Costa Rica (1977, 1985, 1988, 1991, 1994, 1997, 2000, 2003) | Kuwait (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Singapore (1976,1979,1982,1985,1988, 1991,1994, 2004) |
| Croatia (1996, 1999, 2002) | Latvia (1996, 1999, 2002) | Slovak Republic (1995) |
| Cyprus (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Lebanon (1975, 1978, 1981, 1994, 2000, 2003) | Slovenia (1994, 1997, 2000, 2003) |
| Czech Republic (1994) | Liberia (1976,1979,1982,1985) | Spain (1976,1979,1982,1985,1988, 1991,1994, 1997) |
| Denmark (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Libya (1988, 1992, 1995) | Sri Lanka (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Dominican Republic (1976, 1979, 1994, 1997, 2000) | Lithuania (1997, 2000, 2003) | Suriname (1976,1979, 1996, 2003) |
| Ecuador (1976, 1979, 1996, 2002) | Luxembourg (1976,1979,1982,1985,1988, 1991,1994, 1997) | Sweden (1977, 1980, 1983, 1986, 1989) |

**Table A.III.2 (continued)**

| | | |
|---|---|---|
| Egypt (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Macedonia (1997, 2000, 2003) | Switzerland (1985, 1988, 1991, 1994, 1997, 2000, 2003) |
| El Salvador (1976,1979, 1992, 1995, 1998, 2001) | Madagascar (1978, 1981, 1984) | Syrian Arab Republic (1976,1979,1990,1993, 1996, 1999, 2002) |
| Estonia (1994, 1997, 2000, 2003) | Malaysia (1976,1979,1982,1985,1988, 1991,1994, 2000) | Tanzania (1996, 1999) |
| Finland (1976,1979,1982,1985,1988, 1991, 1995, 1998) | Malta (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Thailand (1976,1979,1982,1985,1988, 1991,1994) |
| France (1976,1979,1982,1985,1988, 1991,1994, 1997) | Marshall Islands (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Tunisia (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) |
| Gambia, The (1975,1978,1993, 1996, 1999, 2002) | Mauritania (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000, 2003) | Uganda (1988,1995, 1998, 2002) |
| Greece (1975, 1978, 1988, 1991, 1994, 1997) | Mauritius (1979,1982,1985,1988, 1991,1994, 1997, 2000) | Ukraine (2002) |
| Guatemala (1976,1979,1982,1993,1996, 1999, 2002) | Mexico (1979, 1992) | Uruguay (1999, 2002) |
| Guinea (1975, 1978, 1981,1987, 1990, 1993, 1996) | Micronesia, Federated States of (1988, 1991,1994, 1997, 2000, 2003) | Venezuela (1977, 1980, 1998, 2001). |
| Guyana (1975, 1978, 1981, 1984, 1996, 1999, 2002) | Monaco (1976,1979,1982,1985,1988, 1991,1994, 1997, 2000) | Zimbabwe (2003) |
| Haiti (1975, 1978, 1981, 1984, 1987, 1990) | Mongolia (2000, 2003) | |

Source: Reinhart Rogoff (2004) and Eichengreen and Razo-Garcia (2006) datasets.

**Table A.III.3** **Exit Cases under 2 Models**

| | | MODELS | | | CRITERIA | | EVENTS♥ | | |
|---|---|---|---|---|---|---|---|---|---|
| **Country** | **Time** | **EXIT** | **DGAPT** | **COMBINED*** | **dgapt**** | **dep66** | **CB** | **RCG** | **SP** |
| Algeria | 1988m1 | 0 | 1 | . | 0.9 | 23.3 | | t-4 | |
| Argentina | 1981m3 | 0 | 0 | DISORDERLY | -11.7 | 294.3 | | t=0 | |
| Australia | 1982m8 | 0 | 0 | DISORDERLY | -3.4 | 18.9 | | | 1 |
| Brazil | 1999m2 | 0 | 0 | DISORDERLY | 0.7 | 52.9 | | | |
| Burundi | 1996m5 | 1 | 0 | . | -5.0 | 0.6 | | | 1 |
| Chile | 1982m6 | 0 | 0 | DISORDERLY | -22.1 | 120.9 | t-2 | | |
| Chile | 1999m9 | 0 | 0 | DISORDERLY | -5.2 | 4.5 | | | |
| China | 1981m3 | 1 | 1 | ORDERLY | -4.0 | 3.3 | t=0 | | 1 |
| Colombia | 1983m5 | 0 | 1 | . | -2.5 | 49.6 | | t-3 | |
| Colombia | 1999m10 | 1 | 0 | . | -5.0 | 25.3 | | | |
| Democratic Rep. of Congo | 1975m1 | 0 | 0 | DISORDERLY | -12.0 | 31.6 | | | |
| Costa Rica | 1980m10 | 0 | 0 | DISORDERLY | -6.7 | 119.0 | t=0 | | |
| Czech Republic | 1997M6 | 0 | 0 | DISORDERLY | -5.9 | 27.2 | | | |
| Dominican Republic | 1982m9 | 1 | 1 | ORDERLY | -0.4 | 23.6 | t=0 | | |
| Ecuador | 1982m3 | 0 | 0 | DISORDERLY | -8.1 | 77.5 | | | |
| Ecuador | 1999m2 | 0 | 0 | DISORDERLY | -7.7 | 99.0 | | | |
| El Salvador | 1985m9 | 0 | 1 | . | 1.1 | 180.8 | t=0 | | 1 |
| Greece | 1981m7 | 0 | 0 | DISORDERLY | -5.3 | 26.8 | t=0 | | |
| Guinea | 1999m11 | 1 | 1 | ORDERLY | -0.9 | 22.8 | t-2 | | |
| Haiti | 1993m5 | 1 | 1 | ORDERLY | -6.8 | 44.7 | t-3 | | |
| Iceland | 1975m8 | 1 | 0 | . | -4.1 | 78.1 | | | |
| Iceland | 2000m10 | 1 | 0 | . | 1.5 | 27.8 | | t=0 | |
| Indonesia | 1997m8 | 0 | 0 | DISORDERLY | -16.0 | 282.6 | | t=0 | 1 |
| Iran | 1978m11 | 0 | 0 | DISORDERLY | -18.9 | 45.1 | | t-1 | |
| Iraq | 1981m1 | 0 | 0 | DISORDERLY | -54.7 | 30.7 | | | |
| Italy | 1975m10 | 0 | 1 | . | -2.7 | 60.1 | | | |
| Japan | 1977m2 | 1 | 1 | ORDERLY | 1.5 | -7.9 | | t-4 | |
| Kenya | 1987m1 | 1 | 1 | ORDERLY | 4.2 | 31.5 | | | |
| Korea | 1997m12 | 0 | 0 | DISORDERLY | -12.7 | 59.6 | | t=0 | |
| Lebanon | 1984m3 | 0 | 0 | DISORDERLY | . | 49.9 | | | |
| Liberia | 2000m12 | 0 | 1 | . | 8.7 | 32.1 | | | |
| Madagascar | 1987m6 | 0 | 1 | . | 2.4 | 96.3 | | | |
| Malawi | 1997m7 | 0 | 0 | DISORDERLY | 1.4 | 42.2 | | | |
| Malaysia | 1997m8 | 0 | 0 | DISORDERLY | -11.3 | 52.2 | | | 1 |
| Mexico | 1982m2 | 0 | 0 | DISORDERLY | -10.7 | 352.8 | t=0 | | |
| Mexico | 1995m1 | 0 | 0 | DISORDERLY | -7.4 | 81.2 | t-1 | | |
| Moldova | 1998m8 | 0 | 0 | DISORDERLY | -10.8 | 85.1 | | t=0 | 1 |
| New Zealand | 1985m3 | 0 | 1 | . | -0.2 | -15.8 | | | |
| Nicaragua | 1979m4 | 0 | 0 | DISORDERLY | -22.7 | 157.9 | | | |
| Norway | 1982m8 | 0 | 1 | . | -2.7 | 20.3 | | | |
| Norway | 1992m12 | 0 | 1 | . | -1.1 | 14.9 | | | |
| Paraguay | 1981m9 | 0 | 0 | DISORDERLY | -5.9 | 14.5 | t-4 | | |
| Paraguay | 2000m12 | 0 | 1 | . | 0.4 | 14.4 | | | |
| Philippines | 1983m10 | 0 | 0 | DISORDERLY | -8.9 | 74.3 | t-3 | | |
| Philippines | 1997m7 | 0 | 0 | DISORDERLY | -2.7 | 58.8 | t=0 | | |
| Poland | 2000m4 | 1 | 0 | . | -2.4 | 11.5 | t=0 | t-1 | |
| Russia | 1998m9 | 0 | 1 | . | -6.9 | 266.4 | | | |
| Singapore | 1997m7 | 0 | 0 | DISORDERLY | -4.6 | 22.5 | | t=0 | |
| Slovak Republic | 1998m10 | 0 | 1 | . | -2.3 | 22.2 | | t=0 | |
| Suriname | 1982m5 | 0 | 0 | DISORDERLY | -7.0 | 25.0 | | t-3 | |
| Sweden | 1992m12 | 0 | 0 | DISORDERLY | -5.8 | 34.6 | | | |
| Syria | 1982m6 | 0 | 0 | DISORDERLY | -4.0 | -3.7 | t-1 | t-1 | |
| Thailand | 1997m7 | 0 | 0 | DISORDERLY | -19.5 | 102.9 | | | |
| Turkey | 1980m1 | 0 | 0 | DISORDERLY | -5.0 | 58.1 | t=0 | t-3 | |
| Turkey | 2001m2 | 0 | 0 | DISORDERLY | -5.5 | 107.9 | | | |
| United Kingdom | 1992m9 | 0 | 1 | . | -2.0 | 16.1 | t-3 | | 1 |
| Uruguay | 1982m11 | 0 | 0 | DISORDERLY | -22.9 | 165.8 | t-2 | | |
| Venezuela | 1983m3 | 0 | 0 | DISORDERLY | -3.9 | 225.6 | t=0 | t-4 | 1 |
| Zimbabwe | 1983m7 | 0 | 0 | DISORDERLY | -7.5 | 129.0 | | | |

*Labeled as ORDERLY (DISORDERLY) if case has been placed in orderly (disorderly) nodes by both EXIT and DGAPT models, . otherwise.

**Change in output gap between t-1 and t+1 and depreciation rate between t-6 and t+6

♥ CB: Credit boom peak year vis a vis exit year, t.; RCG: Rapid Credit Growth episode peak year; SP: Stabilization program dummy

**Table A.III.4 Data Description and Source**

| Name | Description | Source | Freq. |
|---|---|---|---|
| Output Gap | Deviation of Output from its HP Trend, GDP constant local currency | WDI, NY.GDP.MKTP.KN | Annual |
| Change in Output Gap | Change in Output gap between t-1 and t+1 | author's calculation | Annual |
| Overvaluation | Deviation of quarterly Real Effective Exchange Rate from its HP trend | IFS | Quarterly |
| Openness | Trade in GOODS and SERVICES (% of GDP) | WDI, NE.TRD.GNFS.ZS | Annual |
| Speculative Pressure Index (Forced) | Weighted average of depreciation, change in interest rate and reserves | R&R(2004) dataset and IFS, 1L.DZF and 60.ZF | Monthly |
| Depreciation Before | Depreciation between t-1 and t-12 | R&R(2004) dataset and IFS line AE.DZF | Monthly |
| Commodity Price Index | Weighted average of Food and Mineral Prices including oil, 2000=100 | UNCTAD Trade Statistics | Annual |
| Trade Balance | Trade Balance as a percentage of GDP | WDI, NE.RSB.GNFS.ZS | Annual |
| Exports to Imports Ratio | | WDI, NE.EXP.GNFS.CD, NE.IMP.GNFS.CD | Annual |
| M2 to GDP ratio | | IFS line 34 and 35 | Annual |
| Liquid Liabilities | Liquid Liabilities as a percentage of GDP | WB Financial Structure Database | Annual |
| M3 to GDP ratio | | WDI, FS.LBL.LIQU.GD.ZS | Annual |
| Incidence of Exits | Incidence of exits in the previous 12 months | author's calculation | Monthly |
| Inflation | | IFS line 64…XZF | Monthly |
| Budget Balance | Budget Balance as a percentage of GDP | WDI, GB.BAL.OVRL.GD.ZS and IFS, line 80.ZF | Annual |
| US Interest Rate | | IFS line 11160B..ZF | Monthly |
| Duration | Number of months under the fixed exchange rate regime before the exit | author's calculation | |
| FDI | Foreign Direct Investment as a percentage of GDP | WDI, BX.KLT.DINV.CD.WD and BOPs | Annual |
| Long-term Debt | Long-term Debt as a percentage of GDP | WDI, DT.DOD.DLXF.CD | Annual |
| Public Debt | Public Debt as a percentage of GDP | WDI, DT.DOD.DPPG.CD | Annual |
| Short-term to Total External Debt | | WDI, DT.DOD.DSTC.ZS | Annual |
| Bank's Liquid Reserves to Assets | | WDI, FD.RES.LIQU.AS.ZS | Annual |
| Depreciation | Depreciation between t-6 and t+6 | R&R (2004), and IFS line AE.DZF | Monthly |
| Exit | Exit dummy equals 1 if country exits, 0 otherwise | R&R (2004), Eichengreen et al. (2006) | |
| Capital Control | Capital Control Dummy | Ghosh et al. (2003) dataset | Annual |
| Concentration | Merchandise Export Concentration Index | UNCTAD Trade Statistics | Annual |
| Current Account | Current Account Balance as a percentage of GDP | WDI, BN.CAB.XOKA.GD.ZS, IMF BOP | Annual |
| Terms of Trade | 2000=100 | WEO (2003), UNCTAD and Ghosh et al.(2003) | Annual |
| Volatility of Terms of Trade Index | Standard deviation of TOT over 5 previous years | | Annual |
| Domestic Credit to Private Sector | Domestic Credit to Private Sector as a percentage of GDP | WDI, FS.AST.PRVT.GD.ZS | Annual |
| Private Consumption | % growth and % deviation from its HP-trend, constant US dollars | WDI, NE.CON.PETC.KD.ZG | Annual |
| Private Invsetment | % growth and % deviation from its HP-trend, constant US dollars | WDI, NE.GDI.TOTL.KD.ZG | Annual |
| Volatility of Investment | Standard deviation of GFC formation to GDP over 5 previous years | IFS line 93E…ZF, and WDI, NE.GDI.FTOT.ZS | Annual |
| Stabilization Program dummy | | Hamann et al. (2005), Calvo and Vegh (1999) | |

## Appendix 4. DGAPT Model

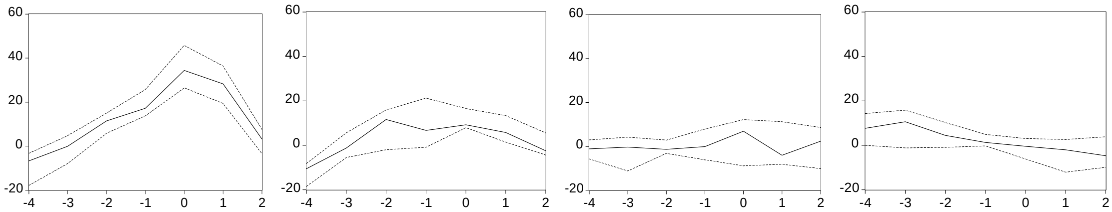
**Figure A.III.2** **DGAPT Model: Selected Variables around Exit time**

**Bold line** : Median **Dashed lines** : Upper and lower quartiles

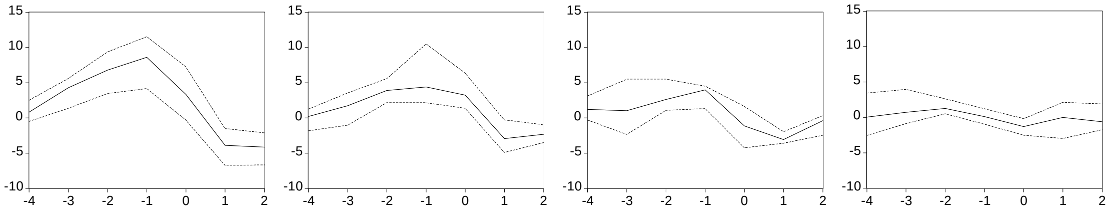
DISORDERLY TNs | ORDERLY TN

*1. Credit Boom* *2. Rapid Credit Gr.* *3. No Boom/Gr.* *4. No Boom/Gr.*

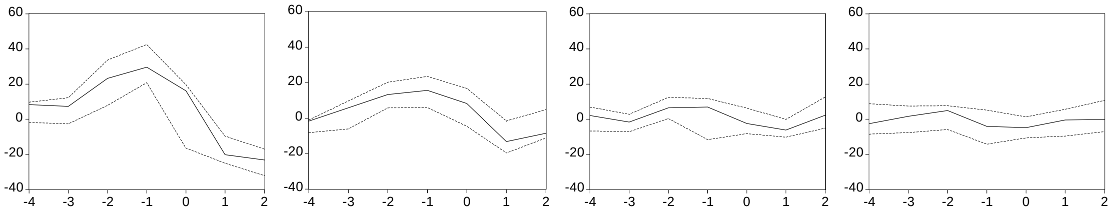
***Real Private Credit***



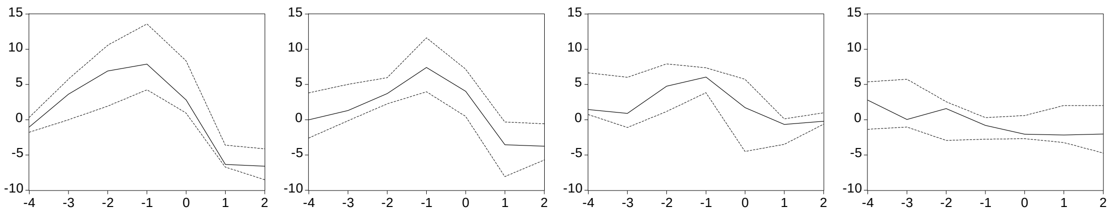

***Real Output***



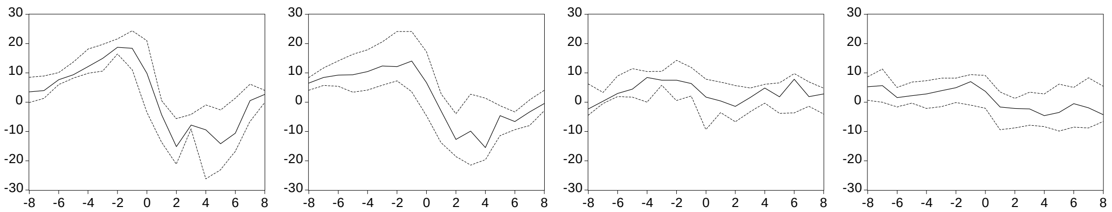

***Real Private Investment***




***Real Private Consumption***




***Real Exchange Rate***




Note: The upper (lower) quartile is the smallest (largest) value of the highest (lowest) 25 percent of all observations in each year (quarter for real exchange rate series). Orderly node under DGAPT model is TN4, disorderly nodes are TN5, TN6 and TN7. See Table A.III.3 for country groupings.

**Appendix 5. Robustness Checks**

**a) EXIT Model**

EXIT Model tree grown with expanded dataset is below.

**Figure A.III.3 EXIT Model Tree under Expanded Dataset**

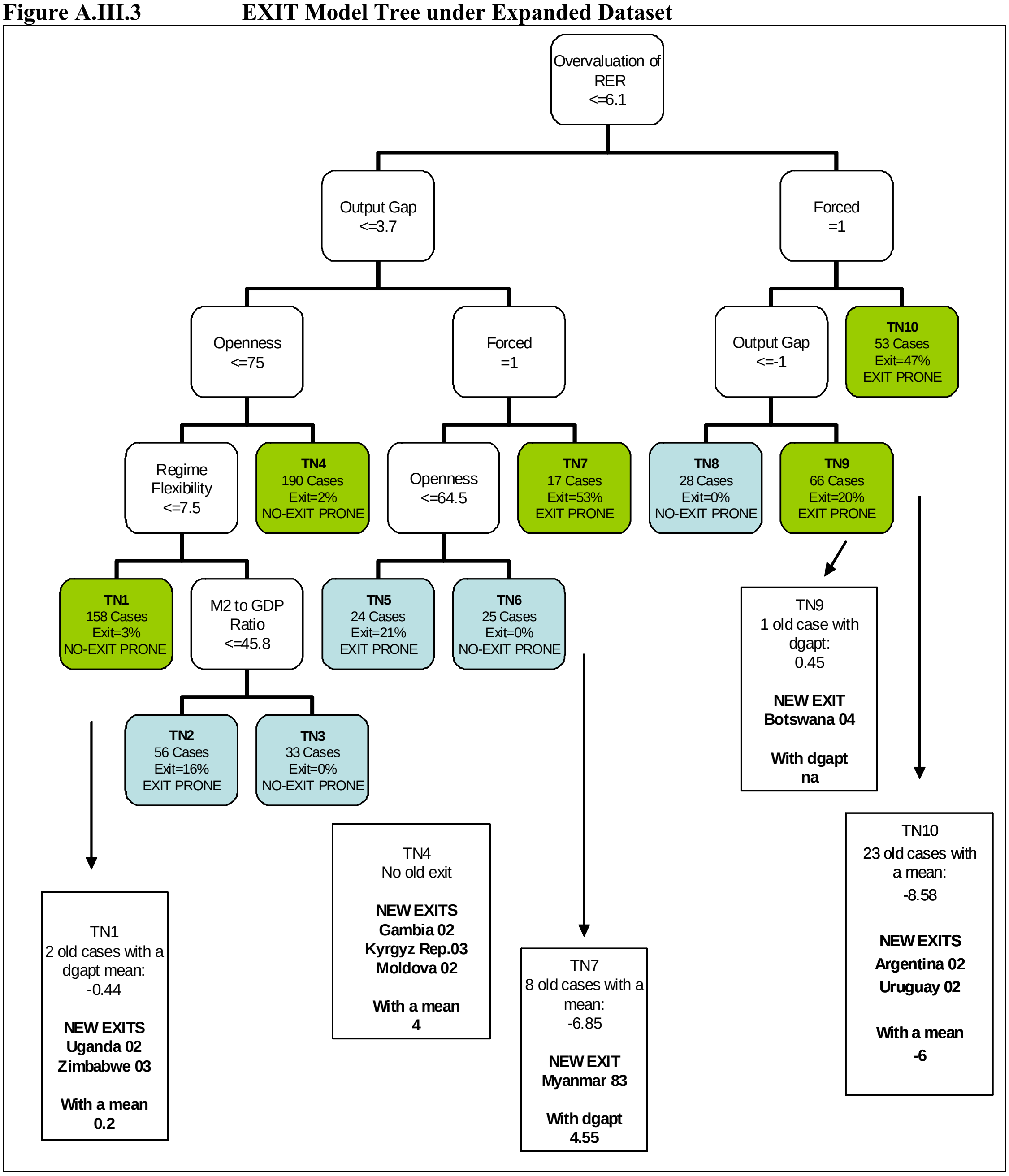



**Figure A.III.4 DGAPT Model Tree under Expanded Dataset**

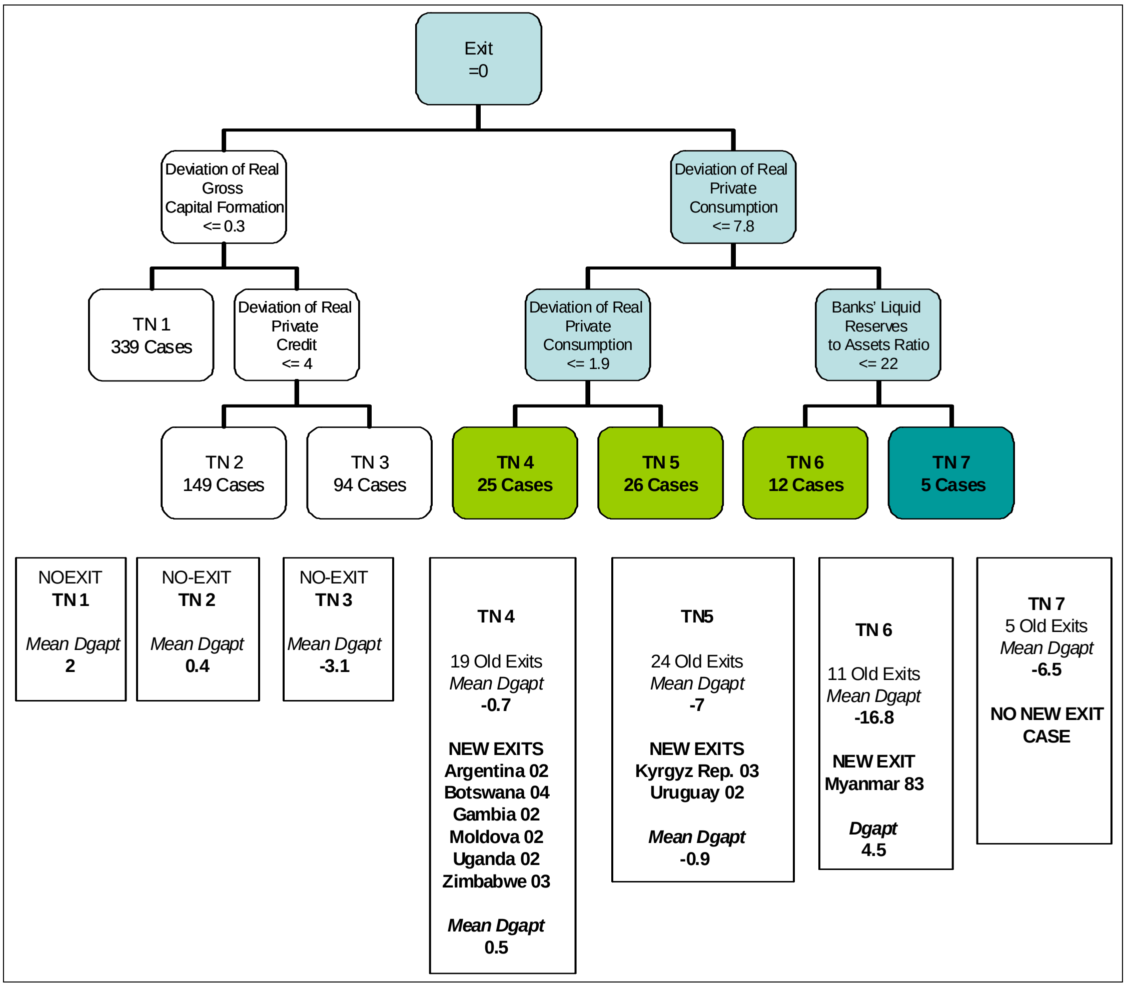
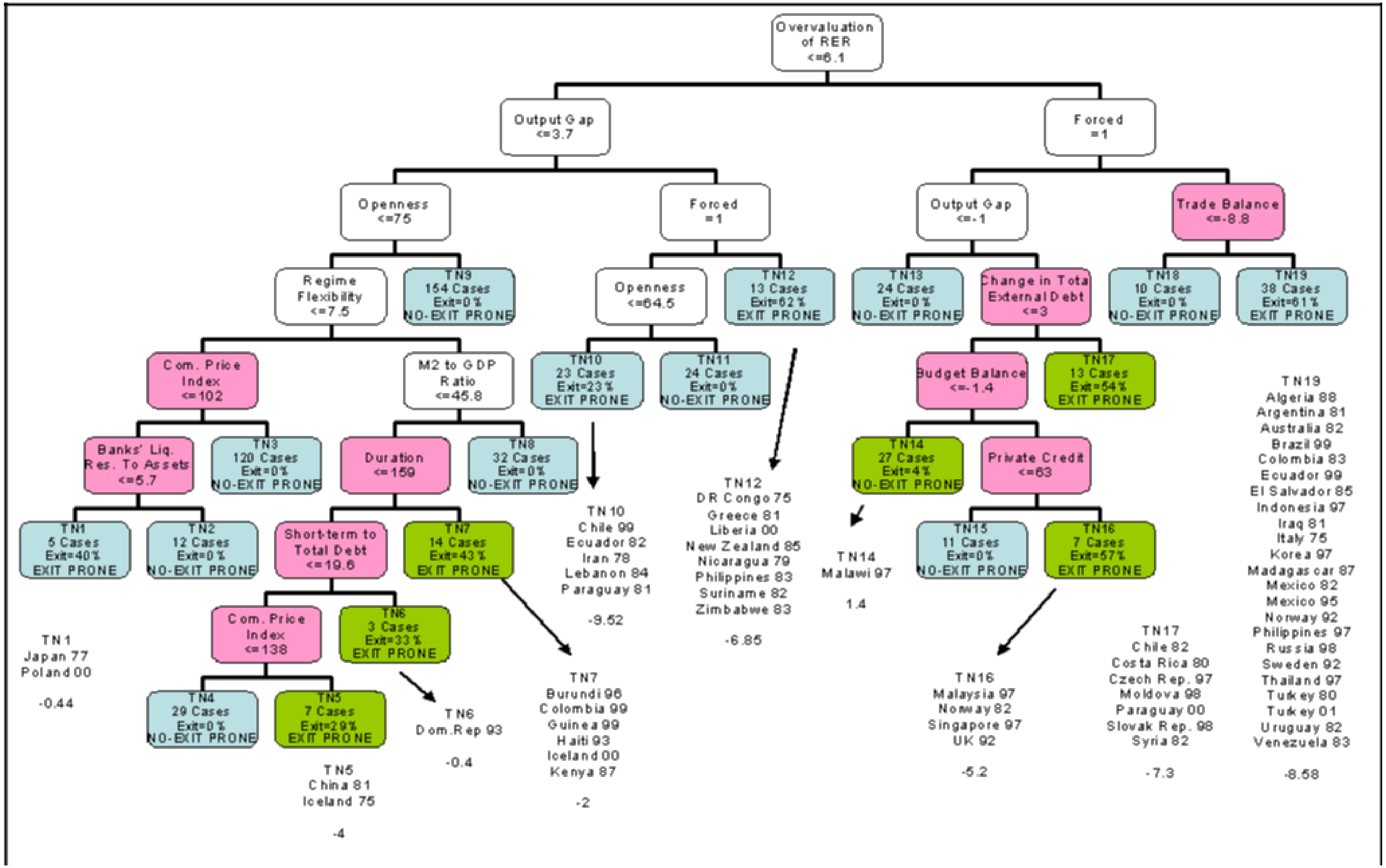

Exit
=0
Deviation of Real
Gross
Capital Formation
<= 0.3
Deviation of Real
Private
Consumption
<= 7.8
TN 1
339 Cases
Deviation of Real
Private
Credit
<= 4
Deviation of Real
Private
Consumption
<= 1.9
Banks' Liquid
Reserves
to Assets Ratio
<= 22
TN 2
149 Cases
TN 3
94 Cases
TN 4
25 Cases
TN 5
26 Cases
TN 6
12 Cases
TN 7
5 Cases
NOEXIT
TN 1
Mean Dgapt
2
NO-EXIT
TN 2
Mean Dgapt
0.4
NO-EXIT
TN 3
Mean Dgapt
-3.1
TN 4
19 Old Exits
Mean Dgapt
-0.7
NEW EXITS
Argentina 02
Botswana 04
Gambia 02
Moldova 02
Uganda 02
Zimbabwe 03
Mean Dgapt
0.5
TN5
24 Old Exits
Mean Dgapt
-7
NEW EXITS
Kyrgyz Rep. 03
Uruguay 02
Mean Dgapt
-0.9
TN 6
11 Old Exits
Mean Dgapt
-16.8
NEW EXIT
Myanmar 83
Dgapt
4.5
TN 7
5 Old Exits
Mean Dgapt
-6.5
NO NEW EXIT
CASE

**Figure A.III.5 Robustness Check: *Tree 4***




Note: *Tree 4* is obtained by changing the minimum child node size option of EXIT tree from 1 to 3, other options were kept unchanged. Note that tree with uncolored parent nodes is the original EXIT tree. Figures below country lists show the average change in output gap around exit year.