An Empirical Analysis of Current Account Data

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Vorwort

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Christian Aßmann

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1. INTRODUCTION

1.1 Object of Investigation

This thesis analyzes certain aspects of the current account balance and its relationship to economic growth. Employing recently developed statistical and econometric techniques for estimation of non linear models, crises phenomena connected to the balance of payments are focused. The analysis of crises phenomena has been subject to tremendous research efforts over the last decades. However, this thesis addresses several empirical and methodological issues, which have received less attention, namely the incorporation of latent heterogeneity and serial dependence structures in empirical models employed for explaining and assessing crises and their influence on economic growth.

Crises are in general recognized as distortive macroeconomic events with many facets. These facets can be distinguished via consideration of different types of crises connected to the balance of payments. The most prominent types of crises discussed within the literature are labeled as current account reversals and currency crises.[1] These crises have in common that their occurrence is either connected to an external shock, or a fragile macroeconomic situation promoting instability and an external and domestic imbalance, or a combination of both. As the balance of payments can be decomposed into current account and capital account, the aim of analysis is not to distinguish, whether the observed balance of payments crises are linked to reverting current account flows, or are rooted in abrupt changes of capital account flows. Naturally, one would suspect the capital flows to trigger at first place the observed reversal as the velocity of these can be expected to be higher than trade flows. Nevertheless, for commodity exporting countries, abrupt changes in world market prices can also cause large changes in the volume of trade flows, which lead changes in capital account flows.

The seminal paper of Krugman (1979) is concerned with explaining the origin of a balance of payments crises and abstracts from foreign assets thus implying the identity of changes in trade flows and the changes of capital flows linked to changes in international reserves. The mechanics introduced by Krugman (1979) are based on the assumption of a central bank pegging the exchange rate. Since the exchange rate influences the relative return for domestic and foreign assets, a rebalancing of investors portfolios towards foreign assets implies the need for an intervention of central banks in order to stabilize the exchange rate. The ultimate source of investors rebalancing of portfolios is rooted in the financing of government budget deficits

[1] Also banking crises and twin crises are discussed within this context focusing on special features of crises events, see Kaminsky and Reinhart (1999), Gorton (1988), Sundarajan and Balino (1991), and Bruinshoofd et al. (2008).

via domestic credit. The expansion of domestic credit reduces the expected return on domestic assets, thus inducing a speculative attack on the central banks stock of international reserves. This basic framework has been extended in various directions, e.g. Flood and Garber (1984) and Claessens (1991) incorporate uncertainty.[2] Since then many others have added to the understanding how balance of payments crises evolve. Obstfeld (1986) added the concept of self-fulfilling crises. Calvo and Vegh (1999) provide an extensive overview, how the lack of credibility in combination with inflation stabilization efforts affect the possibility for crises to occur.

Milesi-Ferretti and Razin (1996) explain the occurrence of a current account reversal via the need for readjustment of external imbalances. The need for adjustment arises from the notion of a country's solvency. Assuming the current account to be balanced in the long run, reversals occur when persistent deficits are perceived as unsustainable. The concept of current account sustainability allows Milesi-Ferretti and Razin (1996) to derive several macroeconomic indicators possibly explaining the occurrence of current account reversals, e.g. changes in terms of trade and a rise in international borrowing costs.[3] These different theories provide the background for identification of explaining variables used for analyzing the determinants of crises in a panel context.

While theoretical work following the above cited models on the potential causes of balance of payments crises is abandon, these models, labeled by Eichengreen et al. (1995) as first and second generation models of crises, do not explicitly provide a modeling of the influence balance of payments crises have on economic growth. The influence of crises on economic growth is in general conceptualized via an induced boom-bust cycle. The boom-bust pattern refers to consumption and investment. Boom-bust cycles in consumption are often discussed in the context of programs of inflation stabilization, see Calvo and Vegh (1999). However, the potential to cause a boom-bust cycle is inherent of any pegged exchange rate system, even when the peg is not part of a stabilization program, see Bordo and Schwarz (1996), Dornbusch et al. (1995), Eichengreen et al. (1995, 1996), Frankel and Rose (1996), Obstfeld (1995), and Sachs et al. (1996).[4] Krugman (1999) discusses some arguments connected to the observation of boom-bust cycles. The argument of moral hazard lending is often put forward to point at deficiencies in the banking sector to explain the occurrence of crises, see also Caprio and Klingebiel (1996). Kaminsky and Reinhart (1999) analyze deficiencies in the banking sector and point at a link between balance of payments and banking crises. Inadequate banking supervision and implicit government guarantees for banks cause massive over-investment in risky projects and excessive consumption. Hence, when the losses come apparent, attacks on the pegged exchange rates are triggered. The resulting drop in consumption and the illiquidity of banks hindering further sustainable investment have the potential to cause a sharp reduction in economic activity. An economic modeling taking explicitly negative real effects of banking crises in an alternative way into account is provided by Chang and Velasco (1998a) based on a model of bank runs suggested

[2] More extensions are given in Eichengreen et al. (1995).

[3] Similar indicators are described by Sturzenegger and Zettelmeyer (2006) for sovereign debt crises.

[4] The subject has also been analyzed earlier in the context of devaluation, see Harberger (1981).

by Diamond and Dybvig (1983). Here, crises stem from the inability of the financial intermediaries to insulate from financial fragility. While these models allow to consider the channels through which crises affect economic growth, empirical investigations allow to quantify these negative effects of crises on economic growth.

Empirical analysis of balance of payments crises has often started with a country perspective focusing on certain crises episodes, which have been disastrous for the involved countries. Famous examples are the Mexican crises and the Argentinian experiences, but also the Asian crises in 1997, which deeply affected Indonesia and Thailand. Blanco and Garber (1986) provide an empirical investigation on a single country level of the model mechanics considered in the theoretical frameworks outlined above. They conduct an estimation of the parameters of the underlying system of difference equations and study the devaluation of the Mexican peso in the late 1970ies and early 1980ies.[5] The empirical evidence supports the underlying mechanics of the theoretical framework and the role of inconsistent economic policies. For further studies of these crises episodes, see Eichengreen et al. (1995) and Radelet and Sachs (1998) among many others.[6] However, according to Bordo et al. (2001), the single country perspective is often not suited due to data limitations to provide the basis for a solid review of the empirical regularities involved in the event of crises, since focusing on single crises events may hinder a correct gauging of macroeconomic environments, which are less favorable to the occurrence of crises. Thus, the natural strategy to broaden the view to a multi crises perspective via adding more observations in time and more countries resulting in a panel data set is straightforward and has been applied in the empirical literature by many authors.[7]

The employed panel data sets can be summarized as follows. Analyzed countries have been industrial, emerging or developing countries, or a mixture of all three kinds. While an extension of the analyzed sample towards more countries and time periods allows to estimate and test more realistic econometric models, which are better suited to capture the regularities of crises, these benefits come at some cost. In contrast to the single country perspective, where most authors have for good reason put emphasis on the institutional and historical particularities of a country under consideration[8], panel studies often neglect or abstract via pooling the panel members from this heterogeneity affecting the data generating process across countries.[9] This may result however in incorrect statistical inference and provides an important motivation for this thesis.

The second extension of data along the time dimension brings also several drawbacks. Starting with the empirical analysis of single crisis events like the crises in the late 1970ies and early 1980ies, the time period has been extended to cover the whole post World War II period.

[5] Further applications of this methodology for single countries are Goldberg (1994), Cumby and van Wijnbergen (1989), Grilli (1990), and Ötker and Pazabaşioğlu (1995).

[6] See also Klein and Coutino (1996), Caprio et al. (1996) and the articles in Journal of International Economics, vol.41, no. 3-4, Symposium on Mexico.

[7] See Calvo (2000), Freund (2000), Gosh and Ostry (1995), and Kray and Ventura (2000) to name a few.

[8] Edwards (1996) studies the case of Mexico in December 1994 and the Chilean experiences in the 1970ies stressing the specific institutional frameworks. For further investigations of the Mexican crises and its institutional particularities, see Calvo and Mendoza (1996), and Dornbusch and Werner (1994).

[9] Often this is due to data limitations with respect to variables capturing the country specific heterogeneity.

Furthermore, attempts to cover the interwar period are documented in the literature as well as the inclusion of data referring to the gold standard era since the 1870ies. While this approach possibly allows interesting comparison of determinants of crises in periods of high capital mobility (the gold standard era exhibits similar properties with respect to capital mobility compared to the 1980ies and 1990ies, see Bordo and Kydland (1995)), the efforts to construct reliable and comparable data sets for these time periods is a subject of own research interest, see Romer (1989) and Bordo et al. (2007) for examples. Given this background on the variety of data sets, empirical studies often focus on officially available data since 1970, see among others Edwards (2001). This thesis follows this line in order to allow for a comparison with recent studies of crises phenomena, see e.g. Milesi-Ferretti and Razin (1998) and Edwards (2004) as prominent examples.

In order to exploit the panel data for consideration of more realistic empirical specifications and to allow for a correct judgement of results with respect to theory, the panel character of the data asks for a cautious specification of heterogeneity across panel members and serial dependence structures within the considered empirical frameworks. Consideration of heterogeneity is important since the often adapted strategy of pooling the different time series across countries leads to biased estimates, when the underlying data generating process can be assumed to differ substantially among countries. Since crises episodes are most often measured as discrete variables, the analysis is thus based on nonlinear discrete choice models, which complicates the modeling of heterogeneity furthermore. The alternative procedure, next to pooling, to use a fixed effects approach is problematic for several reasons. On the one hand, fixed effects are only identified in discrete choice models, when the discrete dependent variable exhibits variability, what is not the case for all countries in the context of crises analysis. On the other hand, consistency of country specific fixed effects requires a relative large time dimension in nonlinear model frameworks, which is also often not present in the considered context causing the occurrence of the incidential parameter problem defined by Neyman and Scott (1948), see Lancaster (2000) for a recent survey. Furthermore, Greene (2004) provides a general analysis of the behavior of the fixed effects estimator for discrete variable models and notes that the problems involved in fixed effects estimation affect all parameters in the model and not only the fixed effects parameters themselves.

Alternative attempts to control for latent heterogeneity are based on fixed effects in a regional context. Countries are classified into regions, (often corresponding to continents) and region specific dummies are included in the regression setup in order to account for regional heterogeneity, see e.g. Milesi-Ferretti and Razin (1998) for such an approach. However, this approach does not allow intra regional heterogeneity. Hence the use of an extended random effects approach to control for this country specific heterogeneity is attractive and so far not documented in the empirical literature on crises connected to the balance of payments. Parameters are modeled as country specific random variables following a common distribution in order to control for latent heterogeneity among countries. This approach has been suggested by Zellner (1968) and elaborated in more detail by Swamy (1970, 1971) and Hsiao (1974) in the context of the linear regression model and is well suited to deal with problems of the fixed effect approach arising in the context of discrete choice models applied in the analysis of balance of payments crises. Applications of this random coefficients approach in the context of discrete choice models are found in Greene and Hensher (2003), Bhat (2000), Erdem (1996), and Train (1999).[10]

The necessity to control for the intertemporal correlation in discrete choice panel models is emphasized by Browning (1992) in order to allow a correct assessment of the influence of explaining variables on the probability of a crises.[11] Structures accounting for serial dependence are considered for two reasons. The occurrence of crises may alter the institutional framework of a country thus altering the occurrence probability of future crises. Also, the considered set of regressors may not be exhaustive. Unobserved factors conceptualized within the error terms of the models may exhibit persistence over time. This persistence has to be incorporated explicitly into the empirical specifications to guard against and inconsistent assessment of the significance of the considered explaining variables capturing erroneously the persistence of unobserved factors.

This thesis therefore provides an empirical analysis incorporating features of latent country specific heterogeneity and serial dependence structures in the employed empirical model frameworks, which have so far not been considered in the literature on costs and determinants of balance of payments crises. Attempts to empirically analyze the determinants of balance of payments crises follow the approach of Frankel and Rose (1996) and apply a panel probit framework. Quantification of the effect of balance of payments crises on economic growth rely often on linear panel regressions, see Milesi-Ferretti and Razin (1998, 2000), Komarek and Melecky (2005) and Gupta et al. (2003). However, this econometric approach does not account for possible endogeneity of the dummy variables indicating the occurrence of crises. Hence, a panel treatment model accounting for these possible sources of mispecification is adapted and extended via the incorporation of serial correlation and latent heterogeneity, following Edwards (2001, 2004) who applies a treatment model to measure the effect of current account reversals on economic growth.

The incorporation of latent heterogeneity and serial dependence structures into the considered non linear model frameworks aiming at explaining crises and assessing the costs of crises causes the occurrence of high dimensional integrals in likelihood based estimation. This thesis utilizes recently developed numerical methods to solve the involved integrational problems, see Geweke and Keane (2001) for a comprehensive discussion. Bayesian methodology is utilized since it allows via the use of Monte Carlo Markov Chain (MCMC) estimation methods a comfortable handling of heterogeneity and serial correlation. The Gibbs sampling procedures developed by Albert and Chib (1993) for the probit model framework are extended to allow for an unbalanced panel structure of the data, for country specific random coefficient, and for serial dependence within the errors. Therefore several modeling devices for the above listed features are incorporated within the probit framework, which have so far not been considered in the empirical literature on balance of payments crises. The developed tools are also used for Bayesian estimation of the treatment framework developed by Heckman (1979), which is hence

[10] Also for single country studies along the lines suggested by Blanco and Garber (1986), Aschheim et al. (1996) advocate the use of time specific random coefficients in the context of linear models.

[11] Hyslop (1999) provides a discussion of serial dependence structures in the context of panel probit models for analyzing female labor force participation decisions. Falcetti-Tudela (2006) incorporate serial dependence structures in panel probit models for explaining the occurrence of currency crises.

extended to allow for latent country specific heterogeneity. The treatment framework seems well suited for an analysis of the effects of balance of payments crises on economic growth, since it allows for correlation in unobservable factors affecting simultaneously economic growth and the occurrence of crises.

This thesis extends the basic treatment framework of Heckman (1979) also towards incorporation of two probit equations, in order to allow an assessment of the joint influence of currency crises and current account reversals on economic growth. The model incorporates possible correlation between shocks influencing currency crises, current account reversals and economic growth. Consideration of this extended treatment model fills a gap in the empirical literature on the effects of currency crises and current account reversals, since is controls via simultaneous analysis and consideration of mutual dependence between currency crises and current account reversals a possible source for mispecification. The necessary identifying restrictions of the model and the considered forms of serial dependence structures make the consideration of a Simulated Maximum Likelihood estimation approach attractive.[12] In order to cope with the considered serial dependence and heterogeneity structures, the resulting integrational problems are solved via setting up an Efficient Importance Sampling scheme developed as an extension of the Importance Sampler of Geweke (1991), Hajivassiliou (1990), and Keane (1993, 1994). The constructed Efficient Importance Sampler follows the work of Richard and Zhang (2007) and Liesenfeld and Richard (2007). The application of an Efficient Importance Sampler as a precise and accurate numerical integration technique is necessary in order to enable correct statistical inference. A transmission of numerical inaccuracy involved in integration on the estimates would hinder a correct assessment of statistical uncertainty via standard asymptotic test procedures.

The above considered analysis of costs and determinants of balance of payment crises relies on identification schemes providing a timing of crises episodes. These identification schemes yield an indicator variable employed as dependent variable for the considered non linear regression models. Identification schemes are either based on a set of ad hoc criteria linked to the time series properties of the current account balance, or based constructed indices, which have been considered in the empirical literature to provide an identification of crises episodes. Only few analysis, see e.g. Bagnai and Manzocchi (1999), are documented in the literature, which aim at an identification of reversal episodes via a full specified empirical model. An empirical model for reversal identification is therefore formulated in terms of a regime switching approach to assess the influence of the considered ad hoc criteria on the identification of reversal episodes. This framework is used to address the problem of robust reversal identification when using ad-hoc criteria. Based on the regime switching framework suggested by Hamilton (1989, 1990) and the extension of Diebold et al. (1994), several possibilities are investigated to account for heterogeneity within the time series properties of the current account balance relative to GDP. Country specific heterogeneity, which is for instance incorporated via a random coefficient approach capturing heterogeneity within the volatility of the considered time series, is neglected when using identical and static ad hoc criteria for identification of reversal episodes via filtering

[12] Application of a full Bayesian approach is computationally less convenient, since closed form sampling is not possible in the considered extended trivariate Treatment model.

the time series for all considered countries.

This thesis therefore considers several modeling devices to match deficiencies concerning latent heterogeneity and serial dependence of the empirical literature on the analysis of balance of payments crises. It discusses possibilities to incorporate latent heterogeneity and serial dependence in the model frameworks used for analysis of the determinants and economic costs of balance of payments crises. The resulting challenges in estimation are addressed via using Bayesian techniques and Simulated Maximum Likelihood estimation, where sampling schemes ensuring accurate statistical inference are developed. The following outline illustrates, how the above mentioned topics are addressed in the following chapters.

1.2 Outline

Chapter 2 focuses on the analysis of the determinants and costs of current account reversals. These sharp reductions of persistent current account deficits have triggered substantial research efforts aiming at explaining the occurrence of current account reversals and assessing their impact on economic growth, see e.g. Milesi-Ferretti and Razin (1998, 2000). Reversals are thereby conceptualized in a way reflecting sustained reductions of current account deficits, therefore taking a long run view on the effects of balance of payments crises on economic growth. The main contribution of this chapter is the application of a Bayesian estimation methodology, which allows a flexible handling of heterogeneity and serial dependence structures. The Bayesian approach provides several methodological advantages, see Koop and Potter (1999) for a discussion. It allows to assess the significance of variables without use of asymptotic results. Also, one is enabled to perform a comparison of non nested model setups arising from the incorporation of latent heterogeneity. Furthermore, model comparison via Bayes factors include an automatic penalty for more complex models, thus providing a protection against highly parameterized models. Hence, a pooled model specification can be compared to the models specification allowing for country specific heterogeneity, although the parameter space of the pooled specification is not a restricted subset of the parameter space of the model specification allowing for latent country specific heterogeneity. The Bayesian methodology also incorporates parameter uncertainty and is suited to combine information contained in multiple peaks in the likelihood, see Hoff et al. (2002) for a short discussion of this feature of Bayesian methodology. In contrast to classical methods where sample uncertainty is approximated locally around the highest peak of the likelihood, Bayesian estimates therefore fully acknowledge the presence of parameter uncertainty in the data.

The literature on current account reversals suggests that several macroeconomic variables connected to current account sustainability can be viewed as explaining variables for the occurrence of current account reversals. Most prominent among these variables are a low stock of international reserves, the terms of trade, and the past current account deficit relative to gross domestic product itself. Recent empirical evidence suggests that reversing current account balances imply costly adjustment processes leading to reduced economic growth. The results concerning the determinants and costs of current account reversals as documented by

Milesi-Ferretti and Razin (1998, 2000) and Edwards (2001, 2004) using pooled and fixed effects estimation are hence reviewed in order to check whether these results are robust against the incorporation of latent heterogeneity and serial dependence structures. The motivation to control for latent heterogeneity across countries arises from the observation that some countries can sustain even high current account deficits as these deficits reflect investment opportunities, i.e. high current account deficits point not for all countries at looming crises. More explicitly, the question is whether the explaining variables documented in the literature are robust, when latent country specific heterogeneity is taken into account. Bayesian specification tests provide evidence in favor of models incorporating latent heterogeneity and serial correlation structures. The results suggest that costs of reversals are overestimated, when country specific heterogeneity is neglected and stress the importance of macroeconomic external variables in explaining current account reversals. Results are checked for robustness against different underlying reversal definitions. The estimation results document a quite high degree of latent heterogeneity across countries, but nevertheless the level of international reserves, the terms of trade, and the current account deficit are robust indicators of current account reversals. It is shown that consideration of latent country specific heterogeneity increases the models ability to explain and identify reversal episodes considerably.

In Chapter 3 the relationship between currency crises and current account reversals is assessed, as well as their joint influence on economic growth. Several empirical studies have been concerned with measuring the effect of either currency and current account crises on economic growth. Only few empirical approaches are documented in the literature providing explicitly a joint analysis of both crises phenomena. Among these are Milesi-Ferretti and Razin (2000) and Komarek and Melecky (2005). The need for a joint assessment of the effect of both crises on growth is connected to the observation that currency crises are often preceded by exaggerated business cycles and capital inflows causing boom-bust cycles of exports and imports, which possibly induce current account reversals. Thus explaining factors for both crises indicators are reviewed in a joint model allowing explicit intertemporal links between the two crises indicators. The consideration of latent country specific heterogeneity and certain forms of serial dependence makes it necessary to employ numerical methods for the calculation of the involved integrals. In particular, the modeling of latent heterogeneity and serial dependence leads to high dimensional normal mixtures. For accurate calculation of the corresponding probabilities given as integrals, an Efficient Importance Sampler is employed and assessed via a Monte Carlo study. The results reveal a large reduction in numerical uncertainty in estimates stemming from Monte Carlo integration. This allows to use standard test procedures for model testing like LR-tests, which would not allow correct inference in the presence of large numerical inaccuracy.

Using several empirical models this chapter serves two aspects. It provides an explicit modelling of crises heterogeneity and controls, via an extended treatment type model, for possible sample selection governing the occurrence of crises in order to estimate the impact on economic growth correctly. The applied empirical models incorporate serially correlated errors and country specific heterogeneity via random coefficients. The results reveal costs in terms of economic growth for both crises. Costs for reversals are linked to country specific variables and shocks explaining current account reversals and growth show significant positive correlation. In relation to Chapter 3, the joint analysis provided in Chapter 4 shows the necessity to consider currency crises as predictors for current account reversals in order to gauge their joint influence on economic growth correctly.

The robustness of ad hoc criteria employed for identification of reversal episodes is subject to Chapter 4. The commonly pursued approach towards the analysis of sharp and persistent reductions of current account deficits relies on ad hoc criteria for identification of reversal episodes, which can be characterized as the transition from an unsustainable to a more sustainable level of current account balance. Instead of using ad hoc criteria based on the time series properties of the current account time series, a full empirical model in terms of a regime switching approach is suggested following Martinez-Peria (2002). Hence, this chapter adapts this alternative framework unifying the matters of reversal identification and analysis of determinants. Regime switching models have been used several times in the literature in the context of financial crises. This paper applies this approach to panel data consisting mostly out of developing countries. Maximum Likelihood estimation of the regime switching model framework is performed using the EM-algorithm and simulation methods based on the filtering and smoothing procedures of Hamilton (1989, 1990) and Kim (1994).

The findings with respect to timing, determinants and costs are compared to those delivered by ad hoc criteria. It is checked, whether the reversal episodes delivered by ad hoc criteria are the same as those identified under the regime switching approach. The analysis reveals two differences. Since the ad hoc approach does not account for country specific volatility of current account balance, as it operates with a fixed threshold value for deficit reduction triggering current account reversals, less reversals are identified under the regime switching approach taking country specific volatility into account. Another point is that the timing based on ad hoc definition of current account reversal episodes using moving averages is up two years later or earlier than for episodes delivered by the regime switching approach. Also a variant of a regime switching model is considered, which provides an alternative way to analyze the impact of a reversal on the path of economic growth. The costs of reversals are therefore assessed in a way taking heterogeneity of countries into consideration, as the model allows for country specific dynamics and volatility. Comparable costs of reversals as documented in the literature are revealed and also the same set of variables shows influence on the occurrence of a reverting current account balance.

Chapter 5 summarizes the main results of this thesis and provides a short outlook.

2. COSTS OF CURRENT ACCOUNT REVERSALS

2.1 Introduction

Current account adjustment processes have been subject to several studies in the empirical literature. Beside studies being concerned with explaining current account phenomena on a national level, see e.g. Calvo and Mendoza (1996), Cashin and McDermott (1996), Calvo et al. (2003) and Ansari (2004), other investigations e.g. by Frankel and Rose (1996) or Hutchinson and Neuberger (2001) analyze the impacts of readjusting current account deficits for the group of emerging countries. Also region specific groups, such as East Asian and Latin American countries, as well as the countries in Central and Eastern Europe have been analyzed, see e.g. Milesi-Ferretti and Razin (1996), Barro (2001), Calvo (2001) and Melecky (2005). Furthermore, with larger data sets becoming available, the impact of reversing current account deficits has been analyzed in the context of large country panels containing not only specific groups. Milesi-Ferretti and Razin (1998) use panel data comprising mostly low and middle income countries to explain the determinants of current account reversals and their influence on economic growth. Utilizing panel data including industrial as well as less developed countries, Edwards (2004, 2005, 2007) highlights the costs of current account adjustment processes.

Identification of explanatory variables of current account reversals is performed via probit regressions, which allow to assess the impact of variables on seldom disruptive events. The set of explanatory variables include external macroeconomic variables, such as openness and the level of reserves, as well as domestic and global macroeconomic variables. Determinants of current account as such have been analyzed by several authors, see e.g. Chinn and Prasad (2003) for a comprehensive overview.

The effect of current account reversals on economic growth has been analyzed either by linear regressions or via treatment models. In a before and after analysis Milesi-Ferretti and Razin (1998) use linear regressions to assess the costs of reversal episodes in terms of economic growth. The results suggest no systematic reduction of growth in the period after a current account reversal. Using a treatment model Edwards (2004) analyzes the costs of a reversal. His results are at odds to those of Milesi-Ferretti and Razin (1998) and suggest that a current account reversal reduces economic growth in the period of occurrence on average by four percentage points and that economic costs of reversals are inversely related to economic openness. While a treatment analysis allows to account for a possible sample selection bias in the occurrence of current account reversals, both studies cited above are less concerned with consideration of latent country specific heterogeneity.

Although panel data sets provide more observations, they often deliver sets of explanatory variables, which are less detailed in terms of institutional particularities than group or country specific studies, see e.g. Calvo (2003), and thus do not capture all heterogeneity, which is likely present in the data. As early as Haberler (1964) noted, the group of less developed countries is still more heterogenous than the group of industrial countries. The studies cited above either use the available exogenous variables to capture institutional particularities of countries or, as these are often not exhaustive for a large panel of countries, use a fixed effects approach. A fixed effects approach for capturing this latent heterogeneity is nevertheless problematic. Some countries do not experience a current account reversal, thus country specific fixed effects are not identified within the probit framework, see Greene (2004) for a general discussion of the behavior and properties of the fixed effect estimator.[1] While for the treatment model a fixed effects approach is in principle applicable within the growth equation, estimation in short panels possibly suffers from the incidential parameter problem studied by Neyman and Scott (1948) and Lancaster (2000). Hence, alternative approaches to deal with unobserved country specific heterogeneity are necessary in order to assess the determinants and costs of reversals correctly.

The aim of this chapter is therefore to analyze possible changes in determinants and costs of reversals, when allowing for a general form of heterogeneity. Via random coefficients, see e.g. Train (2003) for a description of the mixed probit model, unobserved heterogeneity across countries is taken into account. Such a modeling of heterogeneity among countries solves the identification problem of a fixed effects approach for countries where no reversal is observed. Consideration of heterogeneity via this specific form is new in the context of macroeconometric analysis of current account reversals. The empirical literature so far often classifies countries into regions, see e.g. Edwards (2004, 2005), to allow for heterogeneity across specific regions. Random coefficients offer a more flexible, yet parsimonious form of heterogeneity, which is analyzed in this chapter. Next to analyzing the determinants of reversals via a mixed probit model, this chapter reviews the impact of reversals on economic growth via a treatment model. The framework proposed by Heckman (1978) is therefore extended to incorporate heterogeneity via random coefficients.

Furthermore, within the probit and treatment models serial correlation structures are considered. Especially, the errors within the probit equations are modeled as serially correlated. Such an approach towards incorporation of serial dependence allows to account for persistence in unobserved factors summarized within the error terms influencing the occurrence of current account reversals, a feature likely present in the context of macroeconomic event studies as argued by Falcetti and Tudela (2006). The modeling of serially correlated errors provides also access to differences in behavior of unobserved factors arising from different time series characteristics of relative current account balance and measurement concepts employed for description of current account reversal episodes.

This chapter contributes a Bayesian analysis dealing with the matters of heterogeneity and serial correlation in the context of current account reversals. According to Bolduc et al. (1997), Bayesian estimation might be more flexible and faster in the context of mixed probit models

[1] Furthermore, even in case of identified fixed effects, Greene (2004) shows that the Maximum Likelihood estimator in the presence of fixed effects is not well behaved for a small time dimension of the considered panel.

than maximum likelihood approaches and allows furthermore to assess the significance of single variables without relying on asymptotic properties as in a maximum likelihood analysis.[2] For the Bayesian estimation of the treatment model with random coefficients and serially correlated errors as well as for the mixed probit model with correlated errors an approach based on a Markov Chain Monte Carlo (MCMC) technique namely Gibbs sampling is employed.[3] This approach allows to inspect the properties of heterogeneity among countries, as the Gibbs sampling scheme provides the posterior distributions of the random coefficients. Hence, differences in the way some variables affect a countries probability of a reversals can be analyzed. The adequacy of the specifications allowing for heterogeneity and serial correlation is tested by comparing the marginal likelihoods, which are computed according to the methodology proposed by Chib (1995). Furthermore it is highlighted, whether the inclusion of country specific heterogeneity and serial correlation improves the ability of the model to identify reversals. The robustness of results is checked against several alternative definitions of the shift magnitude in current account deficit, which triggers current account reversals.

The results suggest that the consideration of heterogeneity and serial correlation is essential in order to assess the influence of variables correctly. Neglecting heterogeneity furthermore emphasizes the costs of reversals in terms of economic growth.

The outline of the chapter is as follows. Section 2.2 addresses the data set analyzed in Chapter 2 and explains the economic rationale of the determinants of current account reversals and economic growth used in this chapter. Subsection 2.3 describes the frameworks with and without heterogeneity and serial correlation of the probit and treatment model employed for analysis and discusses the corresponding estimation schemes. Section 2.4. gives the Bayesian methodology for model comparison. Section 2.5 presents the empirical findings. Section 2.6 concludes.

2.2 Current Account Reversal Indicators and Economic Rationale of Explaining Variables

Data is taken from the Worldbank World Development Indicators 2005 (WDI) and the Global Development Finance 2004 (GDF) databases. These databases provide annual data ranging from 1960-2004 for a total of 208 (WDI) and 135 (GDF) countries, respectively, but only for a few variables, not including current account balance before 1970. As not all variables of interest are available for each country and each year, an unbalanced panel including less than the possible 135 countries is analyzed. A panel consisting of 963 observations from 60 countries, when all the variables are taken into account, remains. Furthermore a country has to provide at least 10 observations to be included into the panel. The number of observations per country does

[2] Note that a small sample correction while possible via Bootstrap methods appears computationally too burdensome.

[3] Geweke et al. (1997) note that the numerical accuracy of Gibbs sampling in the context of a multinomial multiperiod probit is superior to other approaches based on simulated maximum likelihood or simulated moment conditions in the presence of strong serial correlation. This may provide another argument in favor of using a Bayesian approach.

not exceed 18 periods, since some variables are only available from 1984 onwards. Following Milesi-Ferretti and Razin (1998), Bagnai and Manzocchi (1999) and Edwards (2004) macroeconomic as well as external and global variables are used as explaining variables for reversals and determinants of growth. The following paragraphs describe the included variables in these three categories and shortly review their meanings suggested by different theories. In order to avoid endogeneity problems all variables except the global ones are included with a lag of one period. Furthermore, following Milesi-Ferretti and Razin (1998) the variables current account deficit, GDP growth rate and investment are included in period t as three year averages over the periods $t-3$ to $t-1$.

Current account reversals are defined using several ad hoc criteria.[4] To attenuate the effect of this ad hoc approach, different definitions of current account reversals are considered, four in total. Identification schemes (*I-IV*) are characterized as changes in the average level of current account balance. The definitions follow Milesi-Ferretti and Razin (1998) and Alesina and Perrotti (1997) who apply similar definitions in the context of fiscal stabilization. According to scheme (*I*) a reversal episode in period t is given when the current account balance in t is indeed a deficit and the average current account deficit t to $t+2$ compared to the average current account balance over periods $t-3$ to $t-1$ is reduced by at least 3%. A further restriction is that the deficit level after the reversal does not exceed 10%.[5] Furthermore, in order to measure only sustainable reductions in current account deficit, a reversal is classified in period t only, if the maximum deficit in the three years after the reversal is below the minimum deficit in the three years before the reversal. To avoid that the same reduction shows up twice in the averages, reversal scheme (*II*) allows no further reversal to happen in the two consecutive years after a reversal. Schemes *III* and *IV* differ from scheme *I* and *II* only with respect to the shift magnitude of average current account balance triggering a reversal, which has to exceed 5% now. Tables (2.1) - (2.4) give a complete listing of reversal epsiodes for each country and time period within the considered panel. This different identification schemes imply possibly via consideration of alternative time series properties of relative current account balance different patterns for the unobserved factors influencing the occurrence of current account reversals, which have to hence to be explicitly incorporated within the analysis of determinants of reversals via e.g. serially correlated errors to guard against incorrect assessment of the determinants of current account reversals.

The numbers of reversals identified under the alternative identification schemes are reported in Table (2.5). Entries on the main diagonal provide the number of identified reversals for each of the four alternative schemes, whereas the other entries provide the number of reversals which are jointly identified by alternative schemes. In total, the data summarizes 1312 time periods, as three year averages and no explaining variables are considered. When all identification schemes are applied simultaneously only 53 reversals are identified from a maximum number of 127 reversals under scheme *I*.

[4] Identifying reversals is therefore not data driven as proposed by Bagnai and Manzocchi (1999) who use structural break tests for identification of reversals. Chapter 5 will address the robustness of ad hoc criteria used for reversal identification.

[5] In order to hinder reductions from 30% to 20% of GDP to be identified as reversal episodes.

Given these features of the different identification schemes, they are all used to yield access to the determinants of current account reversals and their effect on economic growth. Variables described in the following serve as a set of determinants for both, current account reversals and economic growth. The set of explaining variables follows the work of Milesi-Ferretti and Razin (1998) and Edwards (2001, 2004).

Included *macroeconomic* variables are economic growth given as the annual growth rate of real gross domestic product (GDP), the share of investment in GDP proxied by the ratio of gross capital formation and GDP, as well as the log GDP per capita in 1975. These variables are considered as determinants of economic growth and current account reversals. The relationship between growth, investment and balance-of-payments is stated in the *balance of payments stages* hypothesis, see the work of Fischer and Franklin (1974) and Halevi (1971). The value of log GDP per capita in 1975 proxies the initial state of development. A less developed country provides investment opportunities what possibly causes current account deficits. High investment can trigger a rise in GDP growth and a country's stock of capital. Thus a country may change in the intercourse of development from a capital importer to a capital exporter. A further macroeconomic variable considered is general government final consumption expenditure as a fraction of GDP. Government consumption is used to proxy the healthiness of the fiscal environment. Since the first generation models of crises, e.g. Krugman (1979) and Flood and Garber (1984), an unsustainable fiscal environment serves as a signal of crises.

The set of *external* variables comprises the current account balance as a fraction of GDP, the share of exports and imports of goods and services in GDP as a measure of trade openness, the share of concessional debt in total debt, interest payments relative to GDP, the share of foreign exchange reserves in imports, the ratio of official transfers to GDP and a terms of trade index (2000=100). In their work on current account sustainability Milesi-Ferretti and Razin (1996) emphasize the effects, which structural features captured by the above variables have on a country's abaility to sustain external imbalances. Already high current account deficits may indicate a higher need for solving these imbalances. A higher degree of openness may enable a country to balance domestic shocks via the current account. As concessional debt is granted by institutional lenders below market conditions, it may provide a source of stabilization for the current account balance. The same argument is valid for granted official transfers relative to GDP. But, as the latter two variables are subject to political decisions they may as well trigger sharp adjustment processes, see Abrego and Ross (2001). Interest payments relative to GDP are included in order to indicate the liabilities a country has to serve. Foreign exchange reserves as stressed by Calvo (1996) play an important role. A low level of reserves may cast doubts whether a country is able to serve its external liabilities. The role of foreign exchange reserves is also prominent in second generation models of balance-of-payments crises, see Obstfeld (1986) among others, in which speculative attacks on the central bank's stock of reserves result inevitably in a balance-of-payments crisis. Changes in the terms of trade may anticipate changes in trade flows. The analytic model of Tornell and Lane (1998) analyzes the effect of terms of trade shocks on current account balance. Their model suggests that a positive terms of trade shock can result in a deterioration of the current account balance thus delaying the occurrence of a reversal.

Global variables taken from the databases are the US real interest rates and the real growth rates of the OECD countries. These two variables shall reflect the state of the world economy and the implied influences on current account readjustments. Rising interest rates may cause higher costs of credits for some countries and therefore lead to current account adjustment. Also a country may be less attractive for foreign investment. A high growth in the merely industrial OECD countries can for example lead to increasing demand for commodities, which may help to reduce some countries deficits. Thus these two variables affect a country's international borrowing constraint. As shown by Atkeson and Rios-Rull (1996) changes in the international borrowing constraint may trigger a balance-of-payments crisis even when macroeconomic policies of a country are consistent.

Table (2.6) summarizes the above described variables via descriptive statistics, i.e. the overall mean and standard deviation.

2.3 Model Description

This section introduces the probit and treatment models used to analyze the determinants of current account reversals and the impact of a reversing current account balance on the growth process. The specified models allow for country specific heterogeneity and/or serially correlated error terms in order to account for the characteristics of the considered panel data. Furthermore, the Gibbs sampling schemes employed in estimation are shortly reviewed.

2.3.1 Probit Model

The determinants of current account reversals are analyzed via probit regressions. This approach allows to assess the influence of a large set of explanatory regressors proposed in the literature on the occurrence probability of a reversal. Starting point is the pooled panel probit model given as

$$\delta_{it} = \begin{cases} 1, & \text{if } \delta^*_{it} \geq 0 \\ 0, & \text{if } \delta^*_{it} < 0, \end{cases} \tag{2.1}$$

where δ_{it} indicates the occurrence of a reversal identified under the different identification schemes for each country $i = 1, \ldots, N$ in each period $t = S(i), \ldots, T(i)$ observed for country i. The latent process δ^*_{it} linking the explanatory variables to the reversal is assumed to follow a linear regression model

$$\delta^*_{it} = X'_{it}\beta + e_{it}, \tag{2.2}$$

where e_{it} is a normally independently identically distributed (iid) error term. If the latent variable δ^*_{it} raises above zero, then a reversal is indicated.

Country specific heterogeneity is incorporated into the model as follows. The parameter vector β is assumed to become a country specific realization of an iid random variable with common mean b and covariance matrix W_b for all countries, i.e.

$$\beta_i \overset{\text{iid}}{\sim} \mathcal{N}(b, W_b), \quad i = 1, \ldots, N. \tag{2.3}$$

Note that W_b can be diagonal assuming independence of the random coefficients.[6] Inclusion of random parameter heterogeneity induces a heteroscedastic covariance structure over time for each individual. Consider the conditional covariance matrix between the latent variables of one individual $\delta^*_{i\cdot}$. The covariance matrix of dimension $(T(i) - S(i) + 1) \times (T(i) - S(i) + 1)$ is given as

$$X'_{i\cdot} W_b X_{i\cdot} + I, \tag{2.4}$$

where $X_{i\cdot} = (X_{iS(i)}, \ldots, X_{iT(i)})$ gathers the variables for country i, and I is an identity matrix denoting the covariance matrix of the latent errors $e_{i\cdot}$. This induced heteroscedastic covariance of the latent variables $\delta^*_{i\cdot}$ implies a different scaling of the latent process in comparison to the pooled specification where the covariance is set equal to I for identifying reasons. Hence, although this different scaling hinders a one to one comparison (with respect to level) of the parameter b with its counterpart obtained from the pooled specification, the influence of latent heterogeneity is highlighted via changes in the evidence for the influence some variables have on the occurrence probability of current account reversals. Using random coefficients allows a general form of country specific heterogeneity, which has the advantage that in contrast to a fixed effects approach, heterogeneity is also permitted for countries not experiencing a reversal. Such an approach possibly highlights how unobserved characteristics of a country, e.g. the institutional framework and political stability among others, alter the influence of a specific variable on the occurrence probability of a current account reversal. Thus the vector b provides the mean influence of reversal determinants when heterogeneity across countries is taken into account. The consideration of a random coefficients approach extends the random effects model of Butler and Moffitt (1982), where a random parameter is assigned only to the constant.[7] However, the random effects model restricts the form of heterogeneity allowed within the model and does therefore possibly not account for all heterogeneity present within the influence of explaining variables.

Furthermore, the case that not all parameters are randomized can be incorporated. The altered model can be described as follows

$$\delta^*_{it} = \overline{X}'_{it}\overline{\beta} + X^{\mathrm{ran}\prime}_{it}\beta_i + e_{it}, \tag{2.5}$$

where superscript X^{ran}_{it} refers to the variables assigned a random coefficient, and $\overline{X}'_{it}$ denote the regressors assigned constant parameters $\overline{\beta}$ respectively. Hence, the probability of a country i being at time t in the observed state δ_{it} is conditional on $\beta_i, \overline{\beta}$ given as

$$P_{it|\beta_i,\overline{\beta}} = \Phi\left((2\delta_{it} - 1)(\overline{X}'_{it}\overline{\beta} + X^{\mathrm{ran}\prime}_{it}\beta_i\right), \tag{2.6}$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. Given the

[6] Within the empirical analysis a diagonal specification will be applied for computational convenience since it allows stable estimation.

[7] Butler and Moffitt (1982) suggest to solve the resulting one dimensional integral in the likelihood via Gaussian Quadrature.

probability $P_{it|\beta_i,\overline{\beta}}$ the likelihood can be stated as

$$L(\cdot|\overline{\beta}, b, W_b) = \prod_{i=1}^{N} \int_{\times(-\infty,\infty)^{\text{ran}}} \left(\prod_{t=S(i)}^{T(i)} P_{it|\beta_i,\overline{\beta}} \right) f(\beta_i|b, W_b) d\beta_i, \tag{2.7}$$

where $f(\beta_i|b, W_b)$ denotes the joint normal distribution of random coefficients β_i depending mean parameter b and covariance W_b and $S(i)$ denotes the first and $T(i)$ the last available period for country i and $^{\text{ran}}$ denotes the number of assigned random coefficients.

Serial correlation capturing different dynamics in latent factors and controlling for different measurement properties of the identification schemes can be introduced in two forms. Neglecting this serial correlation in latent factors summarized within the error terms of this non linear model can cause substantial bias within the estimated parameters.[8] It can be implemented via the error components of the latent model. Alternatively, lagged values of the latent variable δ^*_{it} can be included as explanatory variables. In both forms one needs the unconditional moments of $\delta^*_{iS(i)}$ that is for the first period observed for individual i. These can be computed more easily when serial correlation is modeled within the errors, as the moments of the error distribution are time invariant. In contrast, the moments of the dependent variable δ^*_{it} are time varying, which allows no derivation of the initial moments of $\delta^*_{iS(i)}$. Note also that this problem can not be solved via conditioning on $\delta^*_{iS(i)}$ as it is not observed. Incorporating serial correlation within the error structure is hence modeled as an autocorrelated error process of order one[9]

$$e_{it} = \rho e_{it-1} + u_{it}, \tag{2.8}$$

where u_{it} is an iid normal white noise $(0, 1)$ process. Thus, all errors for country i are jointly normally distributed. The covariance matrix for individual i of the errors $e_{i\cdot}$ is given as

$$\Omega_i = \{\omega_{hj}\}, \quad h, j : 1, \ldots, T(i) - S(i) + 1, \quad \omega_{hj} = \frac{\rho^{|h-j|}}{1-\rho^2}. \tag{2.9}$$

Again, note that the consideration of serially correlated errors implies, similar as for the consideration of latent country specific heterogeneity, a different scaling of the latent process, thus hindering a one to one comparison (with respect to level) of parameter estimates of the different model specifications.

Denoting the occurrence probability for country i conditional on the random coefficients β_i and the fixed parameters $\overline{\beta}$ as $P_{i\cdot|\beta_i,\overline{\beta}}$, this probability is given as the integral

$$P_{i\cdot|\beta_i,\overline{\beta}} = \int_{d(\delta_{iS(i)}, X_{iS(i)}, \overline{\beta}, \beta_i)} \cdots \int_{d(\delta_{iT(i)}, X_{iT(i)}, \overline{\beta}, \beta_i)} \kappa(e_{iS(i)}, \ldots, e_{iT(i)}) de_{iS(i)} \ldots de_{iT(i)}, \tag{2.10}$$

where $\kappa(\cdot)$ denotes a multivariate normal density with mean vector zero and covariance Ω_i, and

$$d(\delta_{it}, X_{it}, \overline{\beta}, \beta_i) = \begin{cases} (-\infty, -(\overline{X}'_{it}\overline{\beta} + X^{\text{ran}\prime}_{it}\beta_i)), & \text{if } \delta_{it} = 0, \\ (-(\overline{X}'_{it}\overline{\beta} + X^{\text{ran}\prime}_{it}\beta_i), \infty) & \text{if } \delta_{it} = 1, \end{cases} \tag{2.11}$$

[8] This is contrary to linear models, where neglect produced inefficient, yet unbiased estimates.

[9] Analysis based on an autoregressive process of order two suggests that one lag sufficiently covers the serial correlation.

defines the corresponding range for integration. The likelihood is thus given as

$$L(\cdot|\overline{\beta}, b, W_b, \rho, X) = \prod_{i=1}^{N} \int\limits_{\times(-\infty,\infty)^{\text{ran}}} P_{i\cdot|\beta_i,\overline{\beta}} \cdot f(\beta_i|b, W_b) d\beta_i, \tag{2.12}$$

where δ and X gather all discrete dependent and explaining variables respectively. Estimation of the considered models via a Bayesian approach is described in the next subsection.

Bayesian Estimation

The Bayesian estimation approach of the probit model via Gibbs sampling, see Albert and Chib (1993), allows a flexible handling of the discussed model features.[10] The high dimensionality of the likelihood integral provides another argument in favor of MCMC methods, as they are well suited for high dimensional integration using the sampling device of data augmentation.[11] Alternative estimation of the probit model via maximum likelihood is used by Milesi-Ferretti and Razin (1998) but without consideration of country specific heterogeneity and serial correlation.[12]

In a Bayesian setup the joint posterior of the parameters is hence proportional to

$$p(\overline{\beta}, b, W_b, \rho|X, \delta) \propto L(\delta|\overline{\beta}, b, W_b, \rho, X)\pi(\overline{\beta}, b, W_b, \rho), \tag{2.13}$$

where $\pi(\overline{\beta}, b, W_b, \rho)$ denotes the prior distribution of the model parameters. Parameter estimates are obtained as the realizations of the moments and quantiles of the posterior distribution. The influence of a variable is assessed via the 95% highest density region of the posterior distribution. The prior distributions incorporate *a priori* information into the estimation. The priors of $\overline{\beta}$, b, W_b and ρ are assumed to be mutually independent and fairly uninformative. Their functional forms are chosen in a way to allow sampling from closed form full conditional distributions. Hence $\pi(\overline{\beta})$ and $\pi(b)$ are multivariate normal with mean zero and a large variance for each element. $\pi(W_b)$ is either Inverted Wishart distributed in case that the random coefficients are mutually dependent, or the product of inverted Gamma distributions in case of mutual independence. The prior for the autocorrelation parameter is uniform. More specifics on the applied prior moments are given in Subsection 2.7.3 of this chapter.

The implemented Gibbs sampler generates draws from the joint posterior of parameters for the considered models by iteratively sampling from the set of full conditional distributions. The parameter set $\theta = \{\overline{\beta}, b, W_b, \rho\}$ is augmented to include the errors of the latent model $\{e_{i\cdot}\}_{i=1}^{N}$. The inclusion of the latent errors linearizes the setup and leads to closed forms for the full conditional distributions of the parameters. For further details concerning the specific forms of the moments of the full conditional distributions see Subsection 2.7.1. The algorithm has hence the following structure:

[10] An introductive illustration of the Gibbs sampling approach is given by Casella and George (1992) and Gefand et al. (1990) in the context of normally distributed data.

[11] Geweke and Keane (2001) give an extensive description of integration methods for latent models.

[12] Falcetti and Tudela (2006) apply a probit model with serially correlated errors and country specific random effect in the context of currency crises. The integration involved in the calculation of the likelihood is performed via the GHK-simulator, see Geweke et al. (1994).

(i) Simulate from $f_i(e_{i\cdot}|\overline{\beta}, \beta_i, X_{i\cdot}, \delta_{i\cdot}, \rho)$ $i : 1 \rightarrow N$, which is a multivariate truncated normal. As serial correlation is modeled via the error structure, the algorithm of Geweke (1991) is used. Draws from the joint distribution of errors are obtained via iterative draws from the set of full conditionals, which are in fact univariate truncated normals incorporating the restrictions $d(\delta_{it}, X_{it}, \overline{\beta}, \beta_i)$, see Equation (2.11). Given the sampled errors one can compute the latent variables as $\delta^*_{it} = \overline{X}'_{it}\overline{\beta} + X^{\text{ran}\prime}_{it}\beta_i + e_{it}$. This linearization of the setup follows Albert and Chib (1993).

- Given the sequences of the error terms, simulate from $f(\rho|\{e_{i\cdot}\}_{i=1}^N)$, which is a truncated normal distribution arising from the equation $e_{it} = \rho e_{it-1} + u_{it}$ and an uniform prior over the interval $(-1, 1)$.

(ii) Simulate from $f_i(\beta_i|X_{i\cdot}, \delta^*_{i\cdot}, \overline{\beta}, \rho)$, $i = 1 \rightarrow N$, which is a multivariate normal distribution arising from the linear model $\delta^*_{it} - \overline{X}'_{it}\overline{\beta} = X^{\text{ran}\prime}_{it}\beta_i + e_{it}$.

- Conditional on the sampled random coefficients $\{\beta_i\}_{i=1}^N$, simulate from $f(b|\{\beta_i\}_{i=1}^N, W_b)$, which is multivariate normal.
- Simulate from $f(W_b|\{\beta_i\}_{i=1}^N, b)$, which is Inverted Wishart distributed. In case that W_b is diagonal, each element is Inverted Gamma.

(iii) Simulate from $f(\overline{\beta}|\{X_{i\cdot}, \delta^*_{i\cdot}, \beta_i\}_{i=1}^N, \rho)$, which is multivariate normal arising from the model $\delta^*_{it} - X^{\text{ran}\prime}_{it}\beta_i = \overline{X}'_{it}\overline{\beta} + e_{it}$.

Note that via dropping steps from this general Gibbs sampling scheme, the Gibbs sampling schemes for the pooled and less general model specifications evolve. After providing the Gibbs sampler for the employed probit model, the treatment model allowing for serial correlation and heterogeneity shall be introduced for the analysis of crises costs.

2.3.2 Treatment Model

A theoretical link between current account reversal as a balance of payments crisis and economic growth has been established by several theoretical models. In contrast to the first and second generation models of Krugman (1979) and Obstfeld (1986), where no such link is provided, third generation models which build upon the experience of the Mexican crisis in 1994 and the Asian crisis in 1998 have provided several channels for a contractionary effect. According to Dornbusch et al. (1995), a current account reversal may cause a disruption of the growth process, as it ends a boom bust cycle caused by an inconsistent macroeconomic policy often linked to a reduction of inflation. Others like Chang and Velasco (1998) and Radelet and Sachs (1998) argue that increasing foreign borrowing causes illiquidity due to deficiencies within the banking sector thus making the countries more vulnerable to panic and sudden loss of confidence, for a detailed discussion see Moreno (1999).

A first step towards measuring the effect of current account reversals on economic growth could be to run growth regressions including the current account reversals indicator as an explanatory variable. However, this approach misses the adaption of several important points arising from the assessment of causal effects. Unobserved factors influencing the growth process and the occurrence of current account reversals, which are conceptualized within the error components of the model, may be correlated and hence influence current account reversals and economic growth. Not accounting for the this mutual dependence results in an erroneous and biased assessment of the causal effect current account reversals have on the economic growth process of a country. A positive correlation among the unobserved factors influencing growth and current account reversals would cause an overestimation of costs, since unobserved factors causing an uprise within the probit equation also show up in the unobserved factors influencing economic growth. The order of magnitude of this transmission depends on the state of considered reversal determinants, as these determine the conditional distribution of unobserved factors given the occurrence of a shock.

Measuring the effect of current account reversals on economic growth is hence done within a treatment model. Heckman (1978) establishes Maximum Likelihood estimation of the corresponding simultaneous equation framework for continuous and discrete endogenous variables. The use of simultaneous equations systems can be traced backed to Haavelmo (1943,1944). This basic framework has also been subject of Bayesian analysis, see among others Rubin (1978) and Imbens and Rubin (1997). Alternative estimation approaches via instrumental variables within this framework are discussed in Angrist et al. (1996). This allows to assess the causal effect of reversals on growth within a system of structural equations in the presence of correlation between latent factors of economic growth and current account reversals correctly. The approach follows Edwards (2004) who considered this model framework to allow for joint consideration of growth and current account reversals taking the possible correlation between shocks causing changes in the probability of a reversal and growth into account.

The purpose of the conducted analysis is to assess the costs of current account reversals when a general form of heterogeneity and serial correlation is considered. This approach allows to take into account differences in the growth process of countries stemming from different institutional as well as historical backgrounds. Also heterogeneity within the determinants of reversals is taken into account as both forms of heterogeneity influence the transmission of shocks between growth and current account reversals.

The model consists of the two equations for economic growth gr_{it} and the latent variable δ^*_{it} for the reversal

$$\begin{aligned} gr_{it} &= Z'_{it}\alpha + \epsilon_{it}, & (2.14)\\ \delta^*_{it} &= X'_{it}\beta + e_{it}. & (2.15)\end{aligned}$$

Within Z_{it} the binary reversal indicator δ_{it} is included to capture the effect of a reversal on growth. The set of explanatory variables in both equations contains the variables described in Section 2.2. The effect of current account reversals on economic growth is correspondingly measured as[13]

$$E[gr_{it}|\delta_{it}=1]-E[gr_{it}|\delta_{it}=0]. \tag{2.16}$$

Since the model incorporates again via a random coefficient approach unobserved heterogeneity of countries stemming from unobserved characteristics, the calculation of the involved expectations is performed within a simulation study as will be explained below. Random coefficients within the growth equation capture differences between countries with respect to growth dynamics. As in the probit model this is achieved via iid random coefficients within each equation, i.e.

$$\alpha_i \sim \mathcal{N}(a, W_a), \qquad \beta_i \sim \mathcal{N}(b, W_b). \tag{2.17}$$

As before, not to all variables a random coefficient has to be assigned. The two equations are therefore altered into

$$\begin{aligned} gr_{it} &= \overline{Z}'_{it}\overline{\alpha} + Z^{\text{ran}\prime}_{it}\alpha_i + \epsilon_{it}, & (2.18)\\ \delta^*_{it} &= \overline{X}'_{it}\overline{\beta} + X^{\text{ran}\prime}_{it}\beta_i + e_{it}. & (2.19)\end{aligned}$$

Within this model serial correlation is incorporated via inclusion of the lagged growth rate gr_{it-1} in Z_{it} and within the error terms of the probit regression for the above considered reasons for controlling latent factor dynamics in the analysis of current account reversals. Hence

$$e_{it} = \rho e_{it-1} + u_{it}, \tag{2.20}$$

and

$$\begin{pmatrix} \epsilon_{it} \\ u_{it} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \psi \\ \psi & 1 \end{pmatrix} \right). \tag{2.21}$$

This modeling of serial correlation allows for rich intertemporal dependencies between the growth process and the process governing the occurrence of current account reversals. Past shocks within the growth equation influence the concurrent latent variable for current account reversals via the assigned contemporaneous correlation and the autoregressive structure of the error component. Correspondingly, past shocks within the latent error process governing the occurrence of current account reversals are transferred via contemporaneous correlation and the lagged growth rates to current values of economic growth. Allowing for such a correlation pattern removes a potential source of mispecification possibly hindering the correct assessment of the effect of current account reversals on economic growth.

[13] More generally, the following expectation need to be calculated

$$\begin{aligned} E[gr_{it}|\delta_{it}=1]-E[gr_{it}|\delta_{it}=0] &= E[Z'_{it}\alpha|\delta_{it}=1]-E[Z'_{it}\alpha|\delta_{it}=0] \\ &\quad + \left[E[\epsilon_{it}|\delta_{it}=1]-E[\epsilon_{it}|\delta_{it}=0]\right]. \end{aligned}$$

See Heckman (1990) for a general discussion of varieties of selection bias.

To perform a Bayesian analysis for the extended treatment framework allowing for random coefficients the likelihood contribution of country i as a constituent part of the posterior distribution is given by the integral

$$L_i(\cdot|a, b, W_a, W_b, \sigma, \psi, \rho, \overline{\alpha}, \overline{\beta}) = \iint\limits_{\times(-\infty,\infty)^{\text{ran}_a+\text{ran}_b}} \kappa_{\epsilon_{i\cdot}}(\epsilon_{iS(i)}, \ldots, \epsilon_{iT(i)}) \tag{2.22}$$

$$\iiint\limits_{d_{iS(i)},\ldots,d_{iT(i)}} \kappa_{e_{i\cdot}|\epsilon_{i\cdot}}(e_{iS(i)}, \ldots, e_{iT(i)}|\epsilon_{iS(i)}, \ldots, \epsilon_{iT(i)}))de_{iS(i)} \ldots de_{iT(i)}$$

$$f(\beta_i, \alpha_i|b, W_b, a, W_a)d\beta_i d\alpha_{i\cdot},$$

where ran_a and ran_b denote the number of random coefficients within the growth and probit equation respecteviley, and the range of integration is defined as

$$d_{it} \quad = \quad \begin{cases} \left(-\infty, -\overline{X}'_{it}\overline{\beta} - X^{\text{ran}\prime}_{it}\beta_i\right), & \text{if } \delta_{it} = 0, \\ \left(-\overline{X}'_{it}\overline{\beta} - X^{\text{ran}\prime}_{it}\beta_i, \infty\right), & \text{if } \delta_{it} = 1; \end{cases} \quad \text{for } e_{iS(i)}, \ldots, e_{iT(i)}. \tag{2.23}$$

However, within the Bayesian estimation this integral has not to be solved, since via augmenting the parameter vector with the latent errors $\epsilon_{i\cdot}$ linearizes the probit setup. Thereby $\kappa_{\epsilon_{i\cdot}}(\cdot)$ denotes the marginal distribution of $\epsilon_{i\cdot}$ given as a multivariate normal distribution evaluated at $gr_{it} - \overline{Z}'_{it}\overline{\alpha} - Z^{\text{ran}\prime}_{it}\alpha_i$ and $\kappa_{e_{i\cdot}|\epsilon_{i\cdot}}(\cdot)$ the conditional distribution of $e_{i\cdot}|\epsilon_{i\cdot}$ given as a multivariate normal with corresponding conditional mean and conditional variance. Given this model setup, the next subsection will shortly provide the Gibbs sampler of this model.

Bayesian Estimation

Detailed specifics on the moments of the full conditional distribution and the corresponding priors are given in Subsection 2.7.2, while the employed prior moments are stated in Subsection 2.7.3. The corresponding Gibbs Sampler, which is employed to simulate from the joint posterior distribution of the model, has the following structure:

(i) Simulate from $f_i(e_{i\cdot}|\alpha_i, \beta_i, X_{i\cdot}, Z_{i\cdot}, gr_{i\cdot}, \delta_{i\cdot}, \epsilon_{i\cdot}, \sigma^2, \psi, \rho, a, W_a, b, W_b)$ $i : 1 \rightarrow N$, which is similar to Step (i) described for the probit model. Nevertheless, here it is derived from a multivariate truncated normal distribution conditional on the observed errors $\epsilon_{i\cdot}$ from the first equation. The serial correlation parameter is drawn conditional on the set of errors from a truncated normal distribution. Given the latent errors, the latent dependent δ^*_{it} is computed to linearize the setup in the following.

(ii) Simulate from $f_i(\alpha_i, \beta_i|X_{i\cdot}, Z_{i\cdot}, gr_{i\cdot}, \delta^*_{i\cdot}, \sigma^2, \psi, \rho, a, W_a, b, W_b, \overline{\alpha}, \overline{\beta})$, $i : 1 \rightarrow N$, which is a multivariate normal distribution. The moments are the same as in a seemingly unrelated regression framework. Given the trajectories $\{\alpha_i, \beta_i\}_{i=1}^N$ one can simulate the underlying parameters a, W_a, b, W_b. The full conditional distributions of a and b are both multivariate normal. The full conditionals of W_a and W_b are either Inverted Wishart, or each element of the main diagonal follows an Inverted Gamma distribution, if the random coefficients are assumed to be mutually independent.

(iii) Simulate from $f(\overline{\alpha}, \overline{\beta}|X_{i\cdot}, Z_{i\cdot}, gr_{i\cdot}, \delta^*_{i\cdot}, \sigma^2, \psi, \rho, a, W_a, b, W_b, \{\alpha, \beta_i\}_{i=1}^N)$, which is a multivariate normal arising from a panel model.

(iv) A difficulty arises in drawing the covariance matrix of the errors from an Inverted Wishart distribution when the element of the main diagonal σ_{22} is restricted to equal 1. The full conditional distribution has to be based on an appropriate prior incorporating this normalizing constraint. This problem has been addressed in several ways, see McCulloch and Rossi (1994), Nobile (2000) and McCulloch et al. (2000) for a discussion of various approaches. In this analysis an identified prior is used as suggested by McCulloch et al. (2000) although for medium large problems empirical experience suggests viability also for a non identified prior scheme suggested by Nobile (2000). Such a scheme would allow direct sampling from a Wishart distribution but unfortunately no accurate calculation of the marginal likelihood. Simulation of σ^2 and ψ is obtained by using a reparametrization of the covariance of ϵ_{it} and u_{it} given as

$$\begin{pmatrix} \sigma^2 & \psi \\ \psi & 1 \end{pmatrix} = \begin{pmatrix} \xi + \psi^2 & \psi \\ \psi & 1 \end{pmatrix}. \tag{2.24}$$

ξ denotes the conditional part of the variance of ϵ_{it} and can be sampled from an Inverse Gamma distribution. Draws of the covariance are obtained via setting up the linear regression $\epsilon_{it} = \psi u_{it} + \zeta_{it}$, where ζ_{it} denotes an error term with variance ξ. Thus, sampling ψ is possible from a normal distribution.[14]

The next section deals with comparison of the different specifications.

2.4 Model Comparison

Within this section, the methods for comparing the different model specifications are introduced. The Bayesian framework allows to compare the different specifications via the marginal likelihood $m(S)$, which gives the evidence of the sample data S under a specific model. This concept incorporates the parameter uncertainty and provides a consistent model assessment even for smaller samples as it is not based on asymptotic properties. The derivation of the marginal likelihood is along the way proposed by Chib (1995).[15] A more general introduction is provided by Kass and Raftery (1995). Starting point of the derivation is to decompose the log marginal likelihood into

$$\ln m(S) = \ln L(\theta^*|S) + \ln \pi(\theta^*) - \ln p(\theta^*|S). \tag{2.25}$$

As this identity holds for all θ, it is calculated at a point θ^* within the highest density region. Within the empirical analysis below θ^* is chosen as the posterior mean.

[14] Further details are given in McCulloch et al. (2000).

[15] The method of Chib (1995) is only directly applicable for Gibbs sampling, as the full conditional distributions have to be completely known. For a generalization of the method applicable to sampling form Metropolis-Hastings algorithm, where the full conditional distributions need only to be known up to a proportional constant see Chib and Jeliazkov (2001).

The first component gives the log likelihood. For the pooled panel probit and treatment model it has a closed form. For the specifications allowing for serial correlation or heterogeneity, the likelihood is computed using the GHK-simulator, see Geweke et al. (1994) or Börsch-Supan and Hajivassiliou (1993) for details.[16] The algorithm consists of the following steps.

(i.a—b) For the probit model simulate M draws $\beta_i^{(m)}$, $m : 1 \rightarrow M$ from $f(\beta_i|b, W_b)$. For the treatment model simulate M draws $\alpha_i^{(m)}, \beta_i^{(m)}$, $m : 1 \rightarrow M$ from $f(\beta_i|b, W_b)$ and $f(\alpha_i|a, W_a)$ respectively.

(ii.a—b) To obtain an estimate of the likelihood of the probit model, the simulator generates M draws from the corresponding multivariate distribution of errors. Therefore, the joint distribution of the errors is split into the corresponding conditional distributions. The approximation has hence the form

$$\tilde{L}_i = \frac{1}{M} \sum_{m=1}^{M} \prod_{t=S(i)}^{T(i)} \kappa(e_{it}^{(m)} | e_{i\cdot\setminus t}^{(m)}, \beta_i^{(m)}), \tag{2.26}$$

where $\kappa(e_{it}^{(m)} | e_{i\cdot\setminus t}^{(m)}, \beta_i^{(m)})$ denotes the corresponding univariate truncated normal distribution conditional on all other elements of the error vector before time period t. The sample information is included in mean and variance of the univariate distribution, which are derived from the multivariate distribution involved in Equation (2.12). For the treatment model the GHK-simulator provides an estimate for the likelihood of one country i corresponding to Equation (2.22) via

$$\tilde{L}_i = \frac{1}{M} \sum_{m=1}^{M} \kappa_{\epsilon_{i\cdot}}(\epsilon_{i\cdot} | \alpha_i^{(m)}) \left(\prod_{t=S(i)}^{T(i)} \kappa_{e_{i\cdot}|\epsilon_{i\cdot}}(e_{it}^{(m)} | e_{i\cdot\setminus t}^{(m)}, \beta_i^{(m)}, \alpha_i^{(m)}) \right), \tag{2.27}$$

where $\kappa_{\epsilon_{i\cdot}}(\cdot)$ denotes the multivariate distribution of the errors of the growth equation and $\kappa_{e_{i\cdot}|\epsilon_{i\cdot}}(\cdot)$ the multivariate distribution of the errors $e_{i\cdot}$ conditional on $\epsilon_{i\cdot}$.

The second component of the decomposed log marginal likelihood is the log prior of all model parameters evaluated at the estimated posterior mean. The last component of the log marginal likelihood is the full posterior distribution of the model parameters $\theta = (\theta_1, \theta_2, \ldots, \theta_K)$ adequately decomposed into blocks of parameters θ_i, $i = 1, \ldots, K$, where parameters within the blocks are sampled together. The full posterior including all integrating constants is obtained via decomposing the posterior distribution into

$$p(\theta^*|S) = p(\theta_1^*|S) \cdot p(\theta_2^*|\theta_1^*, S) \cdot \ldots \cdot p(\theta_K^*|\theta_{K-1}^*, \ldots, \theta_1^*, S). \tag{2.28}$$

Each component of the posterior distribution is estimated as

$$\tilde{p}(\theta_k^*|\theta_{k-1}^*, \ldots, \theta_1^*, S) = \frac{1}{M} \sum_{m=1}^{M} p(\theta_k^*|\theta_1^*, \ldots, \theta_{k-1}^*, \theta_{k+1}^{(m)}, \ldots, \theta_K^{(m)}, S), \tag{2.29}$$

[16] Numerical accuracy of the likelihood estimate is ensured by using 200 replications within the GHK-simulator.

which is the average of the full conditional distribution of θ_k. The trajectories of draws $\theta_{k+1}^{(m)}, \ldots, \theta_K^{(m)}, m = 1 \rightarrow M$ are obtained from running shortened Gibbs sampling schemes. These schemes are shortened in the sense that the parameter blocks $\theta_1, \ldots, \theta_{k-1}$ are not sampled from their corresponding full conditional distributions, but kept constant at their posterior means. For the pooled panel probit model the posterior distribution is provided by the Gibbs output, as only one block of parameters ($\theta = \beta$) is present, i.e.

$$\tilde{p}(\beta|S) = \frac{1}{M}\sum_{m=1}^{M} f(\beta^*|\delta^{*(m)}, S), \tag{2.30}$$

where $f(\cdot)$ denotes the full conditional distribution of β and $\delta^{*(m)}$ denotes the draws of the latent variable. For all other model specifications, the posterior is obtained via running shortened Gibbs runs, where stepwise one full conditional distribution is discarded, see Subsection (2.7.1) and Subsection (2.7.2) for the specific forms of the full conditional distributions. For the specification incorporating serial correlation one additional Gibbs run is necessary, where it is sampled from the full conditional distribution of ρ. When random coefficients are considered, two further shortened Gibbs runs have to be conducted. These principles apply as well to the treatment model, where additional shortened Gibbs runs for the parameters of the error structure have to be added. Given the log marginal likelihood, model comparison is conducted using the scale of Jeffreys' (1961), which classifies the log Bayes factor given as the difference between log marginal likelihoods corresponding to two different model specifications.[17]

Furthermore, the different probit specifications are assessed according to their ability to identify a reversal. It shall be highlighted whether the inclusion of serial correlation and random coefficients improve the ability to indicate a reversal. The ability to indicate a reversal is assessed via estimates of the probability that a reversal occurs in country i in period t given all available information including parameters in period t denoted as I_t. To obtain a simple closed form of this probability, it is calculated as follows

$$\widehat{\Pr}(\delta_{it} = 1|I_t) = \frac{1}{M}\sum_{m=1}^{M} \Pr(\delta_{it} = 1|\overline{X}_{it}'\overline{\beta}^{(m)} + X_{it}^{\text{ran}\prime}\beta_i^{(m)} + \rho^{(m)}e_{it-1}^{(m)}), \tag{2.31}$$

where $\beta^{(m)}$, $\beta_i^{(m)}$, $\rho^{(m)}$, and $e_{it-1}^{(m)}$ are given as draws from the augmented posterior distribution, such that all information available at time t is incorporated via regressors, parameters and latent errors. Note that this probability is provided as a byproduct of the Gibbs sampler. When the estimated probability exceeds 0.5 an observation is classified as a reversal.[18] The ratio of correct and misclassified reversals serves as a model selection criterion. As all explaining variables X_{it}

[17] If $B < 0$ no evidence for the specification under H_0, for $0 \leq B < 1.15$ very slight evidence in favor of H_0 is found, with $1.15 \leq B < 2.3$ the evidence is slight, strong evidence is found for $2.3 \leq B < 4.6$ and very strong evidence is found for $B \geq 4.6$.

[18] Hyslop (1999) highlights the improved ability to fit the observed sequences of the binary variable via comparison of observed and predicted frequencies for all possible sequences of the binary variable in context of a panel with seven time periods. As the number of observations per country ranges for this panel from 10 to 18 the number of possible sequences becomes prohibitively large.

(except the global ones) contain only information up to period $t-1$, this probability highlights the models capabilities to predict a reversal.[19]

2.5 Empirical Results

In this section the estimation results accounting for heterogeneity across countries and serial correlation are presented. Determinants of reversals are assessed via probit regressions following the approach suggested by Frankel and Rose (1996) and Milesi-Feretti and Razin (1998) among others. The impact of reversals on economic growth is analyzed via treatment regressions, see Edwards (2004, 2005). The robustness of findings is checked for different reversal identification schemes as described in Section 2. Therefore reversal schemes I and II refer to a 3% reduction of current account deficits and reversal schemes III and IV to a 5% reduction respectively. For reversal schemes II and IV the consecutive years after a reversal are not allowed to bear a further reversal episode. Comparison of the different specifications is conducted via Bayes factors and the ability of the specifications to predict a reversal. Bayesian estimators are based on a total of 10.000 draws, where inspection of the Gibbs-runs was used to check for convergence. A burn-in phase of 2.000 draws is found to discard the effect of initialization over all models and specifications sufficiently.[20] For a summary of convergence of the Gibbs sequences, see Table (2.17). It provides the diagnostic convergence statistics as introduced by Geweke (1992) for the structural parameters of the most general specifications, i.e. probit and treatment model with serial correlation and random coefficients. The reported convergence statistics indicate convergence for the considered sample of 8000 draws taken from the Gibbs sampling scheme.

2.5.1 Determinants of Current Account Reversals

The estimates for four probit specifications incorporating serial correlation and heterogeneity at different degrees will be discussed in order to highlight the differences in estimation results stemming from the incorporation of serial dependence and latent heterogeneity. Starting point is the pooled panel probit model given in Equations (2.1) and (2.2). The next specification accounts for serial correlation as stated in Equation (2.8). Afterwards, no serial correlation in the errors, but random coefficients modeling country specific heterogeneity described in Equation (2.3) are considered. Finally, a specification incorporating both serial correlation in the errors and random coefficients is estimated.

Table (2.7) reports the results for the pooled panel specification obtained by Bayesian estimation. The upper part of Table (2.7) contains the set of *macroeconomic* variables, which display low explanatory power across all reversal schemes. Only the variable government expenditures becomes significant for reversal scheme I and III respectively. Neither mean growth rate, nor

[19] However, note that the parameters and latent variables are obtained using the full sample information.

[20] All empirical results presented below are broadly confirmed using Maximum Likelihood Estimation. The estimation is performed using the GHK-simulator of Geweke et al. (1994), see for further details Börsch-Supan et al. (1993) and Hajivassiliou (1990). Using 200 replications yields for every model specification similar results as for the Bayesian analysis, although incorporation of parameter uncertainty within the Bayesian methodology causes differences with respect to reached significance levels for several parameter estimates.

investment, nor initial log GDP capturing the initial state of a country's development bear significant influence on the probability of a reversal. Similar results are presented in Milesi-Ferretti and Razin (1998) for maximum likelihood based analysis. Taken together, a country experiencing higher investment and growth in the intercourse of development stages is not exposed to a higher reversal risk. This points out that the macroeconomic state captured by the considered variables seems not to be among the causes triggering current account reversals. In particular the solving of imbalances via reversals appears to be connected to the external state of the economy. This is underlined by the estimation results for the *external* variables given in the middle part of Table (2.7). A higher current account deficit raises the probability to experience a reversal significantly. This is in line with solvency conditions stressed by Milesi-Ferretti and Razin (1996) in their work on current account sustainability. Trade openness as a key variable describing international relationship is not a significant determinant of current account reversals. Thus changes in trade flows seem not to precede current account reversals. Reserves as stressed by Obstfeld (1986) play an important role in lowering the risk of a reversal. Defending a pegged exchange rate against speculative attacks often preceding current account reversals depends on the stock of international reserves, see Sachs et al. (1996) for a discussion in the context of the Mexican crises in 1994.

The role of external debt discussed in Calvo (2005) is captured by official transfers, concessional debt and interest payments. Official transfers and interest payments are not significant across all reversal schemes. In contrast, higher concessional debt has a significant stabilizing effect for reversal schemes II to IV on current account deficits. The higher the fraction of debt gained below market conditions, the longer a current account deficit can be sustained. Concessional debt is often provided by institutional lenders and generally constitutes a component of debt with low volatility and long maturity. This in line with the view of Cole and Kehoe (2000) who show in their model the impact of high volatile, short maturity debt on the occurrence of a crises. The terms of trade index has also a significant negative impact on the occurrence probability of a reversal across all reversal definitions. This is in line with the view of Tornell and Lane (1998) that higher terms of trade can lead to further deficits. Furthermore, higher export prices reflected in the terms of trade may allow to sell of a country's debt via trade. Higher terms of trade contribute therefore to the credibility of a country, what is an important factor stressed by Guidotti and Vegh (1999).

The results for the *global* variables are given in the lower part of Table (2.7). Higher US real interest rates and OECD growth rates raise the probability of a reversal, although significant only for reversal scheme I, where only a 3% reduction in current account deficit triggers a reversal. Changes in a countries borrowing constraint implied by these variables seem to influence only smaller deficit reductions. Differences occur between reversal schemes I and II, which rely both on a 3% reduction of current account deficit, but refer to different restrictions of reversal dynamics. In scheme I, the aftermath of a reversal is not strictly excluded from bearing a further reversal episode. This definition allows a reversal episode to happen over several years. Thus changes in a country's borrowing constraint seem to trigger only adjustment processes spanning several years.

The results for the specification accounting for serial correlation are given in Table (2.8). The estimation results document a strong positive correlation for reversal schemes I and III where only the dynamic behavior of current account in the aftermath of a reversal is restricted. Negative correlation is found for definitions II and IV, which restrict the two consecutive periods to bear no further reversals. Note that correlation is not showing influence within scenario IV. This pattern of positive and negative correlation in the unobserved factors captured within the error terms seems to be due to the different restrictions on the aftermath of a reversal implied by the different reversal schemes. These different restrictions build on different measurement concepts of current account reversals utilizing alternative time series properties of the relative current account balance. Note that the incorporation of this serial dependence within the errors is necessary in order to gauge the influence of determinants of current account reversals correctly.[21] Table (2.16) summarizes the log marginal likelihoods for all estimated model specifications. Corresponding Bayes factors provide mixed evidence in favor of serial correlation across the different reversal schemes. While strong to very strong evidence is provided for schemes I and III, no evidence can be found for reversal scheme II and IV. The considered serial correlation may account for persistent unobserved heterogeneity. This unobserved heterogeneity might provide an intertemporal link between crises, which is important to account for according to Falcetti and Tudela (2006). The above reported evidence suggests that this issues are more prominent in reversal schemes I and III, although the estimated correlation is significant for reversal scheme II. Changes with respect to the determinants of reversals compared to the pooled specification occur only in OECD growth rates and government expenditures. Both become overall insignificant. As these variables are likely to be highly correlated over time, they seem to capture in the pooled specification part of the serial correlation in the dependent variable linked to persistent unobserved heterogeneity.

After accounting for possible persistent unobserved heterogeneity via correlated errors, unobserved heterogeneity among countries shall be addressed via modeling of random coefficients. Given the low variation of the dependent variable implied by the low number of reversals specification of all parameters as random coefficients would possibly stress the data too much. In particular, random coefficients are therefore assigned to the mean current account deficit, the level of reserves and official transfers. Some economic arguments shall be provided to motivate this specific choice.[22] High current account deficits are noted as an indicator of crises, but may also reflect that a country's investment opportunities are not restricted by domestic saving and that this investment is expected to create output, which allows a country to meet its future obligations. Revealed heterogeneity in the influence of the level of reserves on the occurrence of reversals could stem from different exchange rate regimes and different policy strategies that a country has adapted for inflation stabilization, see Calvo and Vegh (1999). The effect of official transfers might be heterogeneous as it proxies the quality of public sector institutions and

[21] In contrast to linear models, where neglect of serial correlation results in inefficient, yet unbiased estimates, neglect of serial dependence in the nonlinear discrete choice framework can cause serious bias in estimated parameters.

[22] A Maximum likelihood analysis with heteroscedastic variance modeled as $\sigma_{it} = \exp\{\gamma X_{it}\}$ points in the same direction.

therefore accounts for differences in the general institutional background of a country.

Bayesian estimates are given in Table (2.9). The findings with respect to the evidence for the influence of macroeconomic and global variables are unchanged when compared to the two former specifications. Again the importance of the external variables is stressed. The estimated variances of the three random coefficients range from 0.019 to 0.114 implying a considerable degree of heterogeneity, which will be discussed in detail below. Interestingly via consideration of a random coefficient in connection to the official transfers, this variable becomes overall significant. In contrast, the variable concessional debt becomes insignificant over all reversal schemes. Given that concessional debt variable has the highest ratio of between country variance to total variance, these findings suggest that the role of a country's debt situation in explaining reversals depends on unobserved heterogeneity. Unobserved heterogeneity also alters the influence of interest payments, which is now significantly positive for reversal scheme III. Bayes factors provide across all reversal schemes strong to very strong evidence in favor of incorporation of unobserved heterogeneity via random coefficients compared to the two former specifications. Note that this specification of heterogeneity is also strongly preferred against the inclusion of regional dummies within the pooled specification (estimation results not reported here), which is often used within the literature to capture region specific heterogeneity.[23] The corresponding marginal likelihoods for the different reversal schemes are -393.23, -322.74, -302.10 and -247.13 (for scheme I to IV). The heterogeneity connected to the mean level of current account deficit before the reversal accounts for the ability of some countries to maintain deficits over a considerable period of time. Their institutional background, e.g. within the financial sector as analyzed by Kaminsky and Reinhart (1999), seems to provide a stable environment, such that deficits do not raise the risk of a reversal. Thus the estimated heterogeneity in connection with the significant mean confirms Fischer's (1988) caution that the "primary indicator [of a looming crises] is the current account deficit". For the level of reserves, the random coefficient approach matches two possible sources of heterogeneity. The heterogeneity of the influence of reserves accounts for differences between countries with pegged and flexible exchange rates. Also, this influence might differ as for some countries the reserves are managed by central banks with a varying degree of independence from politics.

Finally two specifications allowing for heterogeneity and serial correlations shall be considered. The first one builds upon the specifications described above and includes all explaining variables. The second specification is more parsimonious and includes only the external variables. This parsimonious specification illustrates that only these variables are needed to identify the actually observed reversals, see discussion below. Bayesian estimation results are given in Table (2.10) and in Table (2.11) for the more parsimonious specification focusing on the external variables. All variables show similar behavior and significance as in the above discussed specifications. The estimated serial correlation parameter is again positive for reversal scheme I and III, while negative for reversal scheme II and IV. Also the estimates of the parsimonious specification show similar results for the external variables and the estimated correlation. Comparing

[23] This approach has to be based on an ad hoc classification of countries into regions. Often regions refer to continents, which is problematic for some countries due to their institutional background.

the model specification incorporating serial correlation and country specific heterogeneity with the previous ones shows that these specifications are to be preferred according to the marginal likelihood, see Table (2.16). This stresses the importance of country specific heterogeneity and serial correlation in order to obtain an adequate model representation for explaining current account reversals.

The next paragraph discusses the improved ability of the models to identify reversals, when serially correlated errors and random coefficients are considered. The criterion to classify a period as a reversal period is given in Equation (2.31). Table (2.12) gives the number of identified reversals under the four considered model specifications incorporating latent heterogeneity and serial correlation at different degrees. While in reversal scheme I the pooled specification 10 out of 100 reversals are correctly classified, the serial correlation specification classified 19 out of 100 correctly. The latter also reduces the number of incorrect classified periods from 105 to 88. The specification with heterogeneity improves further. The number of identified reversals increases to 29 while 78 periods are incorrectly classified. The ratio of correctly classified reversals increases from 89,1% for the pooled specification to 91,9% for the heterogenous specification. The parsimonious specification incorporating serial correlation and a random coefficient identified 24 reversals correctly and 84 periods incorrectly. It provides therefore a better classification of reversals than the pooled and serial correlation specification, but performs slightly worse than the heterogenous specification. For reversal scheme II all different specifications can identify only a lower fraction of reversals (at most 10% compared to 27% under reversal scheme I). Especially the specification with serially correlated errors cannot improve when compared to the pooled specification. This also confirms the results obtained from the marginal likelihoods for this reversal scheme, where no evidence was found for serially correlated errors. The heterogenous specification performs best and the parsimonious specification is second best. For reversal scheme III and IV the parsimonious specification is found to classify reversals best and the heterogenous specification is performing second best, although the overall performance to identify reversals is quite poor, especially for reversal scheme IV.

Since Bayesian estimation is performed via sampling from the posterior distribution of the parameter vector, which is augmented to include the random coefficients, the output from the Gibbs sampler allows to access the form of country specific heterogeneity contained within the panel data set. Figure (2.1) shows the distribution of the sampled country specific coefficients for the current account level, the level of reserves and official transfers for all panel members (upper panel). Especially the influence of the mean current account on the occurrence of a probability differs between countries. For some countries current account deficits have no impact on the probability of a reversal. Differences in the impact of current account deficits on the probability of a reversal may be due to the different institutional frameworks, which are not accounted for by observable variables. In the lower panel, the distribution of the sampled mean effect is shown for the three variables. This allows to assess which countries show atypical behavior.

Summarizing, incorporation of heterogeneity and serial correlation affects the analysis of determinants of current account in two ways. It stresses the importance of the external variables in explaining reversals and improves the models' ability to indicate the observed reversals.

2.5.2 Costs of Current Account Reversals

The relationship between economic growth and current account reversals, which is established in the third generation models of balance-of-payments crises, see Calvo and Vegh (1999) and Krugman (1999) among others, is analyzed via treatment regressions in order to measure the costs of a reversal in terms of economic growth. The applied methodology allows to assess the impact of a parsimonious parameterized form of heterogeneity and serial correlation on the estimated costs of a reversal. Firstly, the results are reviewed for a pooled specification ignoring heterogeneity, see Equations (2.14) and (2.15). Afterwards, the relationship is investigated allowing for serial correlation in the probit equation (Equation 2.20). Finally, results for a specification incorporating heterogeneity via random coefficients, Equation (2.17 - 2.19), and serially correlated errors are discussed. The set of explanatory variables for the probit equation is taken from the analysis of determinants of current account reversals.

The Bayesian estimates for the pooled model specification are given in Table (2.13). For all considered reversal schemes, the correlation between the two equations is significant, varying from about 0.66 in scenarios I/II to approximately 0.41 in scenarios III/IV. Such a contemporaneous correlation implies that changes or shocks within the unobserved components subsumed within the error terms of the model simultaneously affect both processes governing economic growth and the occurrence probability of a current account reversal.

In the growth equation several variables which are also considered within the probit equation serve as covariates. For instance, openness is considered as an explaining factor for economic growth, as well as investment captured by gross capital formation relative to GDP and initial GDP per capita in 1975. Investment and openness are found to be overall significant, with larger openness and higher investment enhancing growth. The estimates for the influence of a reversal on economic growth captured by the reversal dummy range within the pooled specification from 6.99 for the second reversal scheme to 4.56 for reversal scheme IV, which is at the upper end of the estimates reported in the literature. Following Edwards (2001, 2004), it is of interest to study, whether a more open economy is less severely influenced by reversal than more closed economies. As the highest density regions for the variable trade openness times the reversal indicator across all reversal schemes do not exclude zero at any conventional level, the Bayesian results do not support the hypothesis that higher openness reduces the costs of reversals.

Within the joint analysis of reversals and economic growth provided by the treatment framework, the results concerning the determinants of reversals are in line with those obtained in the pooled probit regressions. All variables have expected signs, with minor changes in the significance level for some variables, e.g. growth shows now positive and significant influence on the occurrence probability of a reversal in identification schemes I and III.

Estimation results for the treatment model incorporating serial correlation within the probit equation are given in Table (2.14). Similar to the results for the pooled treatment specification, correlation between equations is significantly positive for all reversal schemes. The serial correlation parameter is again positive for reversal schemes I and III and negative for reversal scheme II and IV, although it is significant only for reversal scheme I and III. This is in line with the results obtained from the probit regressions incorporating serial correlation. However, the magnitude of the serial correlation is diminished, when compared to the results obtained from the probit regressions. This can be explained by the imposed correlation structure between the two equations allowing the transition of past and contemporaneous growth shocks towards the reversal equation. Compared to the pooled treatment model, inclusion of serial correlation reduces the correlation between the equations and estimated costs slightly. Differences in all other estimated parameters are only minor. Comparison of the marginal likelihood reveals strong evidence for the inclusion of serial correlation within reversal scheme I, while no or only weak evidence is found in reversal schemes II to IV. These results sofar underline the necessity to to perform a joint analysis of reversals and growth, since the serial correlation captures persistence in unobserved factors influencing the probability of current account reversals, which are now characterized via contemporaneous correlation between economic growth and current account reversals.

The discussion of results for the specification considering heterogeneity and serial correlation simultaneously is based on a slightly more parsimonious specification of the probit equation focusing on the external variables.[24] The necessity to control panel growth regression for various structures capturing heterogeneity has been emphasized by the empirical literature on economic growth, see among others Mankiw et al. (1992) and Barro (1991, 1996). As emphasized by Barro (1996) the control for heterogeneity is necessary in order to allow a correct judgement of "*the necclassical model's central idea of conditional convergence* ... [where] *poorer countries grow faster per capita once one holds constant measures of government policy, initial levels for human capital, and so on*". While the above cited literature focusses on a long run view of economic growth, Lee et al. (1998) argue in favor of a heterogeneous growth dynamics, which is likely present due to institutional particularities and different historical backgrounds for instance. Therefore, within the growth equation random coefficients capturing latent heterogeneity are assigned to the constant and the lagged growth rate, thus capturing heterogeneity within the country specific growth processes concerning level and dynamics, which is not fully reflected within the determinants of economic growth. Within the probit equations random coefficients capturing latent heterogeneity are again connected to the current account deficit, the level of reserves and the concessional debt. The corresponding estimation results of this specification are given in Table (2.15).

The findings with respect to the reversal coefficient and the parameter governing the correlation between the two equations differ substantially compared to the other treatment specifications. The consideration of random coefficients incorporating latent country specific heterogeneity results in a heteroscedastic covariance structure within the growth and probit equations and thus provides a different shock structure linked to the occurrence of reversals compared to the pooled specification. The highest density region of the parameter capturing the influence of the reversal indicator on economic growth does not any longer exclude zero as in the speci-

[24] Note that results have been checked also for the full specification (estimation results not reported here) revealing similar results. The log marginal likelihoods are given in Table (2.16), see the line referring to the full specification.

fications not concerned with latent country specific heterogeneity. However, the interpretation of the estimated parameter coefficients as reversal costs is subject to some caveats, as discussed in detail within the following paragraphs. Also, the highest density region of the parameter capturing the influence of investment does now include zero. These variables therefore seem to have captured some heterogeneity, which is now related to the heterogeneity captured by the random coefficients.

The marginal likelihood indicates that including heterogeneity via random coefficients is the preferred model structure for all identification schemes, see Table (2.16). This underlines the importance to consider heterogeneity in order to measure the costs of a reversal correctly. In order to check the robustness of findings against the underlying prior assumptions concerning the variance of the random coefficients, the estimation is performed for two alternative prior scenarios denoted as • and ••. Prior • assigns larger expected mean and variance to the variance parameters of the random coefficients, while prior •• assigns smaller expected mean and variance compared to the baseline scenario, see Table (2.19) for details on the considered hyperparameters of prior distributions.[25] The estimated reversal coefficient and correlation parameters were similar across the different prior specifications (also for all other parameters) and the marginal likelihoods given in Table (2.16) indicate strong evidence in case of all priors for consideration of heterogeneity via inclusion of random coefficients. The estimates for parameters of determinants of current account reversals and economic growth (not reported here) behave similar compared to the previous prior specifications and also no evidence is found for a systematic link between costs and trade openness.

As mentioned above, some important caveats apply to interpreting the parameters capturing the effect of the reversal indicator on economic growth directly as overall costs of reversals. The effect of current account reversals on economic growth is conceptualized as

$$\begin{aligned} E[gr_{it}|\delta_{it}=1]-E[gr_{it}|\delta_{it}=0] &= E[Z_{it}\alpha|\delta_{it}=1]-E[Z_{it}\alpha|\delta_{it}=0] \\ &\quad +E[e_{it}|\delta_{it}=1]-E[e_{it}|\delta_{it}=0]. \end{aligned} \tag{2.32}$$

This decomposition shows that the economic costs of reversals are correctly indicated by the estimated parameter linked to the reversal indicator only if the occurrence of the reversal crises is not linked to unobserved shocks captured by the error components of the model. Hence, if occurrence of a reversal is induced via a positive shock in the unobserved error component, this shock transfers to the growth equation via the contemporaneous correlation, thus reducing the immediate impact of the reversal indicator. The reversal indicator within the growth equation therefore characterizes costs of reversals, which are induced via changes in the explaining variables of a reversal, which is not a typical reversal episode. As the ability of the probit models to detect reversals is limited within the specifications not incorporating latent country specific heterogeneity, see the analysis in the previous section, several reversals within the observed sample can only be explained via the occurrence of movements within the unobserved factors, which are summarized within the error component of the analyzed model frameworks.

[25] Priors of mean parameters are not subject to sensitivity analysis, since they are chosen to be generally uninformative with a variance of 1000.

Furthermore, the growth equation is dynamic, costs are hence not only induced within the period of occurrence of a reversal, but also in the following periods, thus making the sequential evaluation of the above expectations necessary. Therefore costs of reversals are assessed via the expected values

$$E\left[\sum_{t=t_0}^{t^*} gr_{it}|\delta_{it_0}=1\right] - E\left[\sum_{t=t_0}^{t^*} gr_{it}|\delta_{it_0}=0\right] = \tag{2.33}$$
$$E\left[\sum_{t=t_0}^{t^*} Z_{it}\alpha_i|\delta_{it_0}=1\right] - E\left[\sum_{t=t_0}^{t^*} Z_{it}\alpha_i|\delta_{it_0}=0\right] + E\left[\sum_{t=t_0}^{t^*} e_{it}|\delta_{it_0}=1\right] - E\left[\sum_{t=t_0}^{t^*} e_{it}|\delta_{it_0}=0\right],$$

where t_0 denotes the occurrence period of a current account reversal and t^* defines the considered time span, which is investigated for assessment of economic costs induced by current account reversals. The involved expectations are assessed via simulation.[26] Furthermore, since costs involved within the occurrence of a typical current account reversals shall be assessed, the two regressor profiles are chosen to mimic typical behavior in case of a current account reversals and in case that no current account reversal occurs. To capture a typical no reversal environment for economic growth of a country, a regressor profile for both equations is constructed via calculation of country averages over periods when no reversals are observed. Likewise, to mimic a typical situation for the occurrence of a reversal episode, a regressor profile for both equations is constructed using country averages for periods given the occurrence of a reversal and the following periods in the aftermath of a reversal. The consideration of these artificial environments representing typical situations of reversal and no reversal occurrence with in the sample allows to assess average costs over time given in the different model specifications.[27]

The simulation of the necessary expectation is hence performed as follows. Given the constructed environments, a sample of errors ensuring the occurrence of a reversal in an initial period are simulated for the pooled specification and the specification incorporating latent country specific heterogeneity.[28,29] Also a random sample from the distributions of random coefficients is generated, which is then matched with the sample of errors providing a trajectory of growth. In total one thousand samples of size one thousand are generated and used for calculation of the mean effect as the well as the distribution of the effect of current account reversals on economic growth via computation of sample averages.

Table (2.18) gives the simulated costs of reversals derived as the difference between the current account reversal scenario for economic growth and the typical no reversal scenario of

[26] An analytical solution to the corresponding integration problem is not available although the error of the probit and growth equation are jointly normally distributed what would allow to compute the expectations $E\left[\sum_{t=t_0}^{t^*} e_{it}|\delta_{it_0}=1\right]$ and $E\left[\sum_{t=t_0}^{t^*} e_{it}|\delta_{it_0}=0\right]$ conditional on the random coefficients defining the range of integration. However, the succeeding integral over the random coefficients has then no closed form solution.

[27] Note that this approach in dealing with the regressors also incorporates in an ad hoc manner reactions of the weak exogenous regressors, e.g. the reserve variable, on a current account reversal.

[28] Sampling of errors is performed based in two steps. The joint distribution of errors is decomposed in the marginal distributions of errors within the initial period t_0 and the corresponding conditional distributions of all other considered errors.

[29] Consideration of the specification incorporating serial correlation within the errors of the probit equation yields similar results compared to the pooled specification and are hence not presented.

economic growth. Figure (2.2) provides a graphical illustration of the corresponding time pathes of reversal costs. The upper part of Table (2.18) corresponds to the results referring to the pooled specification, while the lower part gives the results for the model incorporating latent country specific heterogeneity and serial correlation. The results indicate smaller differences in estimated reversal costs than focusing on parameter estimates linked to reversal indicators would suggest. This highlights the different characterizations of shocks for the different model specifications linked to the occurrence of current account reversals. However, costs highlighted by the pooled specification are slightly higher compared to costs gauged on the consideration of the specification concerned with the incorporation of latent country specific heterogeneity. For this specification, the first period effect as well as the (cumulated) overall effect corresponding to four years does not exclude zero from the 95% bands of the simulated mean effect. However, the 95% bands for the two specifications are overlapping.

Concerning the costs of a reversal in terms of economic growth the results suggest that neglecting country specific growth dynamics leads to higher estimated costs as when heterogeneity is incorporated, since the shocks influencing the occurrence of current account reversal are altered across the different model specifications. Moreover, the incorporation of random coefficients yields the preferred model specification. Thus these results are in line with the results of Milesi-Ferretti and Razin (1998) who also report no systematic slowdown of growth in the aftermath of a reversal. However, they are at odds with those of Edwards (2004) obtained under classical estimation of the treatment model. Although the estimated costs for the treatment model incorporating serial correlation and heterogeneity are comparable (2%-4%), the incorporation of parameter uncertainty lowers estimated costs for all reversal schemes.

2.6 Summary

Bayesian analysis allows a flexible handling of unobserved heterogeneity and serial correlation. The necessity to model heterogeneity via random coefficients arises from the data set, since not all countries experience a reversal thus leaving a fixed effects approach unidentified. The Bayesian framework also offers the possibility to compare the different model specifications without relying on asymptotic properties and provides small sample inference accounting for parameter uncertainty. The findings suggest that incorporating country specific heterogeneity and serial correlation is essential to meet the macroeconomic character of the panel data set and to assess the determinants and costs of a reversal correctly. Results for the probit regressions suggest that inclusion of serial correlation is necessary to account for the correlation pattern induced via the different reversal definitions building on different measurement concepts for reversal identification linked to alternative dynamic restrictions of the dynamics of relative current account balance. Consideration of unobserved heterogeneity, which also implies a form of serial correlation, leads to a preferred specification highlighting the importance of the external variables in explaining the occurrence of a reversal. The form of country specific heterogeneity given as a byproduct of the Gibbs output reveals that for some countries the probability of a reversal does not depend on the current account deficit although the estimated mean effect is highly significant. A possible explanation may arise from the differences in the country specific institutional backgrounds, which are hardly accessible via observable variables. Furthermore, via the incorporation of heterogeneity the model's ability to indicate the observed variables is improved. Latent heterogeneity and serial correlation therefore provide a parsimonious way to incorporate country specific heterogeneity due to unobserved variables.

The treatment analysis reveals that costs in terms of economic growth are overestimated when latent heterogeneity modeled via random coefficients is neglected. The sample selection found in the pooled specifications is not present when country specific dynamics are allowed. Thus, within the preferred model specification, no strong evidence for a negative effect of current account reversal on economic growth is revealed compared to the specifications not concerned with latent country specific heterogeneity. Also more open countries do not seem to suffer less from a reversal than more closed economies. As the evidence provided by the analysis is in favor of accounting for latent heterogeneity, further attempts should aim on linking this kind of heterogeneity to observed variables.

Tab. 2.1: Listing of reversal episodes and analyzed countries – 1972 to 1986 (1)

	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
Argentina	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Bangladesh	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Benin	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0
Bolivia	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Botswana	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	1 1 0 0	0 0 0 0
Brazil	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0	0 0 0 0	0 0 0 0
Burkina Faso	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Burundi	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Cameroon	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Central African Republic	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Chile	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
China	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0
Colombia	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	1 1 0 1
Congo. Rep.	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Costa Rica	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	1 1 0 0	0 0 0 0	0 0 0 0
Cote d'Ivoire	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	1 1 0 0	0 0 0 0	0 0 0 0
Dominican Republic	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0	0 0 0 0	0 0 0 0
Ecuador	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0
Egypt. Arab Rep.	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
El Salvador	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0
Gabon	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Gambia. The	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	1 1 1 1	0 0 0 0	1 1 0 0	0 0 0 0	0 0 0 0
Ghana	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Guatemala	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Guinea-Bissau	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0
Haiti	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0	1 0 0 0
Honduras	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0
Hungary	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0
India	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the four reversal definition are given in the sequence I, II, III and IV.

Tab. 2.2: Listing of reversal episodes and analyzed countries – 1972 to 1986 (2)

	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
Indonesia	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0
Jordan	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Kenya	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Lesotho	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Madagascar	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Malawi	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Malaysia	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	1 1 0 0
Mali	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Mauritania	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Mexico	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Morocco	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1
Niger	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0
Nigeria	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0
Pakistan	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Panama	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Paraguay	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Peru	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Philippines	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0
Rwanda	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Senegal	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0
Seychelles	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Sierra Leone	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0
Sri Lanka	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0
Swaziland	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0
Thailand	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0
Togo	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Tunisia	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1
Turkey	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Uruguay	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Venezuela. RB	x x x x	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0
Zimbabwe	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	1 0 0 0

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the four reversal definition are given in the sequence I, II, III and IV.

Tab. 2.3: Listing of reversal episodes and analyzed countries – 1987 to 2002 (1)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Argentina	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	x x x x
Bangladesh	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Benin	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x
Bolivia	0 0 0 0	1 0 1 0	1 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	x x x x
Botswana	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x
Brazil	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Burkina Faso	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Burundi	x x x x	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Cameroon	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Central African Rep.	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Chile	1 1 1 1	1 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	x x x x
China	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Colombia	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	x x x x
Congo. Rep.	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	x x x x
Costa Rica	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Cote d'Ivoire	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 1 0 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	x x x x
Dominican Republic	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Ecuador	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Egypt. Arab Rep.	1 0 1 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	x x x x
El Salvador	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Gabon	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x
Gambia. The	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Ghana	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	x x x x
Guatemala	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Guinea-Bissau	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Haiti	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Honduras	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Hungary	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
India	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the four reversal definition are given in the sequence I, II, III and IV.

Tab. 2.4: Listing of reversal episodes and analyzed countries – 1987 to 2002 (2)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Indonesia	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Jordan	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	1 1 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Kenya	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Lesotho	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x
Madagascar	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Malawi	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Malaysia	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Mali	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x
Mauritania	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Mexico	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Morocco	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	x x x x
Niger	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x
Nigeria	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x
Pakistan	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	1 1 0 1	1 1 0 0	x x x x
Panama	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	x x x x
Paraguay	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Peru	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	x x x x
Philippines	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Rwanda	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Senegal	1 0 0 0	1 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Seychelles	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	1 1 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Sierra Leone	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Sri Lanka	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 0 1 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Swaziland	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Thailand	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	1 1 1 1	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Togo	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x
Tunisia	1 1 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Turkey	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Uruguay	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Venezuela. RB	0 0 0 0	0 0 0 0	1 1 1 1	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x
Zimbabwe	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	0 0 0 0	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x	x x x x

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the four reversal definition are given in the sequence I, II, III and IV.

Tab. 2.5: Number of reversals under different identification schemes

	positive reversals			
	I	*II*	*III*	*IV*
I	127	86	82	56
II	–	86	53	56
III	–	–	82	53
IV	–	–	–	56
all	53			
# of observations	1312			

Notes: Reversals refer to a reduction of deficits; (all) gives the number of reversals identified under all schemes; (I) – refers to a 3% reduction of average current account over a period of three years when the maximum deficit after the reversal is below the minimum deficit before the reversal (II) – refers to a 3% reduction of average current account over a period of three years with no reversal allowed in the consecutive two years (III) – refers to a 5% reduction of average current account over a period of three years when the maximum deficit after the reversal is below the minimum deficit before the reversal (IV) – refers to a 5% reduction of average current account over a period of three years with no reversal allowed in the consecutive two years .

Tab. 2.6: Summary statistics of variables - Chapter 2

variable	mean	standard deviation
mean current account deficit	-3.8729	6.0807
mean investment	21.4777	7.8048
initial log GDP in 1975	2.8320	2.0253
government debt	13.2801	5.4704
trade openness	65.3319	37.7830
reserves	3.5739	3.1443
official transfers	4.2004	7.0542
concessional debt	35.5962	26.7426
interest payments	2.9349	2.1628
terms of trade	110.2295	39.2025
US real interest rates	5.9603	1.1164
OECD real growth rate	3.0519	0.9360
# of observation	963	
time period	1973-2002 (unbalanced design)	

Tab. 2.7: Pooled probit model - Bayesian estimates

	I	*II*	*III*	*IV*
constant	**−3.2336*** (0.8493)	**−2.4587*** (0.9449)	**−2.4867*** (0.9684)	**−1.8293** (1.0862)
		macroeconomic		
mean growth rate	0.0140 (0.0206)	−0.0045 (0.0231)	0.0282 (0.0239)	0.0077 (0.0267)
mean investment	−0.0010 (0.0106)	0.0078 (0.0119)	0.0129 (0.0122)	0.0128 (0.0142)
initial log GDP	0.1277 (0.0893)	0.0646 (0.0983)	0.0734 (0.1043)	0.0337 (0.1176)
government	**0.0233*** (0.0118)	0.0100 (0.0135)	**0.0301*** (0.0133)	0.0173 (0.0153)
		external		
mean current account deficit	**−0.0609*** (0.0120)	**−0.0457*** (0.0130)	**−0.0525*** (0.0125)	**−0.0416*** (0.0140)
openness	−0.0018 (0.0022)	−0.0012 (0.0024)	0.0002 (0.0024)	0.0003 (0.0027)
reserves	**−0.0784*** (0.0305)	**−0.0553** (0.0337)	**−0.1102*** (0.0392)	**−0.1215*** (0.0464)
official transfers	−0.0084 (0.0104)	−0.0039 (0.0113)	0.0071 (0.0115)	0.0129 (0.0127)
concessional debt	−0.0050 (0.0042)	**−0.0079** (0.0047)	**−0.0125*** (0.0053)	**−0.0177*** (0.0063)
interest payments	0.0239 (0.0306)	−0.0020 (0.0350)	0.0529 (0.0332)	0.0188 (0.0372)
terms of trade	**−0.0032*** (0.0017)	**−0.0033** (0.0019)	**−0.0075*** (0.0024)	**−0.0063** (0.0026)
		global		
US real interest rate	**0.1303*** (0.0532)	0.0673 (0.0600)	0.0523 (0.0593)	0.0246 (0.0671)
OECD growth rate	**0.1413*** (0.0714)	0.1240 (0.0814)	0.0935 (0.0806)	0.0832 (0.0925)
log(marg-lik)	-381.3095	-308.7889	-295.4025	-244.0496

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.8: Probit model with serial correlation - Bayesian estimates

	I	*II*	*III*	*IV*
constant	$-$**3.7337*** (1.7891)	$-$**2.4967*** (0.9110)	-1.6105 (2.5208)	$-$**1.8703** (1.0337)
		macroeconomic		
mean growth rate	0.0058 (0.0319)	-0.0066 (0.0224)	0.0332 (0.0389)	0.0090 (0.0269)
mean investment	0.0102 (0.0223)	0.0079 (0.0113)	0.0172 (0.0314)	0.0130 (0.0140)
initial log GDP	0.2105 (0.1970)	0.0577 (0.0934)	0.0097 (0.3007)	0.0282 (0.1095)
government	0.0100 (0.0208)	0.0103 (0.0121)	0.0190 (0.0250)	0.0196 (0.0144)
		external		
mean current account deficit	$-$**0.0898*** (0.0235)	$-$**0.0460*** (0.0120)	$-$**0.0973*** (0.0314)	$-$**0.0422*** (0.0135)
openness	-0.0048 (0.0047)	-0.0011 (0.0023)	0.0002 (0.0060)	0.0003 (0.0026)
reserves	$-$**0.1646*** (0.0717)	$-$**0.0565** (0.0313)	$-$**0.2894*** (0.1414)	$-$**0.1241*** (0.0456)
official transfers	-0.0056 (0.0152)	-0.0057 (0.0111)	0.0162 (0.0189)	0.0125 (0.0124)
concessional debt	-0.0073 (0.0085)	$-$**0.0084** (0.0044)	$-$**0.0282** (0.0165)	$-$**0.0190*** (0.0065)
interest payments	0.0452 (0.0438)	-0.0040 (0.0332)	0.0857 (0.0536)	0.0105 (0.0377)
terms of trade	$-$**0.0076*** (0.0038)	$-$**0.0035** (0.0018)	$-$**0.0153*** (0.0066)	$-$**0.0064** (0.0023)
		global		
US real interest rate	**0.1941** (0.0813)	0.0763 (0.0606)	0.1123 (0.0984)	0.0326 (0.0697)
OECD growth rate	0.1343 (0.0977)	0.1249 (0.0813)	0.0972 (0.1161)	0.0825 (0.0943)
ρ	**0.6390*** (0.0742)	$-$**0.2682*** (0.1203)	**0.7263*** (0.0883)	-0.2486 (0.1647)
log(marg-lik)	-357.0324	-307.3159	-262.4228	-244.2613

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.9: Probit model with partial heterogeneity - Bayesian estimates

	I	*II*	*III*	*IV*
constant	**−3.4913*** (1.7002)	**−3.3853** (1.7983)	**−3.4977** (2.0291)	−2.8575 (2.0265)
		macroeconomic		
mean growth rate	0.0399 (0.0332)	0.0240 (0.0356)	0.0734 (0.0445)	0.0598 (0.0477)
mean investment	0.0007 (0.0217)	0.0102 (0.0223)	0.0180 (0.0260)	0.0123 (0.0267)
initial log GDP	0.2092 (0.1943)	0.1723 (0.2044)	0.2161 (0.2360)	0.1378 (0.2323)
government	0.0279 (0.0211)	0.0285 (0.0232)	0.0346 (0.0272)	0.0428 (0.0294)
		external		
mean current account deficit	**−0.2274*** (0.0392)	**−0.1583*** (0.0371)	**−0.1946*** (0.0455)	**−0.1389*** (0.0443)
$\sigma^2_{\text{mean CAD}}$	0.0262 (0.0074)	0.0212 (0.0063)	0.0273 (0.0080)	0.0228 (0.0068)
openness	−0.0062 (0.0041)	−0.0040 (0.0041)	−0.0039 (0.0042)	−0.0037 (0.0043)
reserves	**−0.2453*** (0.0731)	**−0.2134*** (0.0798)	**−0.3493*** (0.0966)	**−0.3476*** (0.0955)
$\sigma^2_{\text{reserves}}$	0.0384 (0.0144)	0.0346 (0.0143)	0.0454 (0.0226)	0.0377 (0.0177)
official transfers	**−0.1244*** (0.0467)	**−0.1536*** (0.0521)	**−0.1295*** (0.0554)	**−0.1526*** (0.0623)
$\sigma^2_{\text{official transfers}}$	0.0288 (0.0095)	0.0279 (0.0089)	0.0308 (0.0121)	0.0312 (0.0119)
concessional debt	−0.0018 (0.0078)	−0.0052 (0.0084)	−0.0005 (0.0114)	−0.0129 (0.0127)
interest payments	0.0676 (0.0483)	0.0092 (0.0582)	**0.1767*** (0.0623)	0.0824 (0.0668)
terms of trade	**−0.0126*** (0.0038)	**−0.0095*** (0.0038)	**−0.0159*** (0.0049)	**−0.0102*** (0.0046)
		global		
US real interest rate	**0.1477*** (0.0694)	0.1108 (0.0793)	0.0490 (0.0824)	0.0560 (0.0902)
OECD growth rate	**0.1676** (0.0930)	0.1506 (0.1031)	0.0504 (0.1103)	0.0369 (0.1228)
log(marg-lik)	-352.6263	-300.7738	-258.3797	-229.1459

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.10: Probit model with partial heterogeneity and serial correlation - Bayesian estimates

	I	*II*	*III*	*IV*
constant	$\mathbf{-4.0967}$	$\mathbf{-3.3704}^*$	-3.2196	-2.2565
	(2.5838)	(1.5991)	(2.9546)	(1.8493)
		macroeconomic		
mean growth rate	0.0416	0.0198	0.0732	0.0461
	(0.0401)	(0.0301)	(0.0468)	(0.0383)
mean investment	0.0117	0.0127	0.0185	0.0112
	(0.0305)	(0.0190)	(0.0352)	(0.0201)
initial log GDP	0.2956	0.1414	0.1258	0.0666
	(0.2888)	(0.1781)	(0.3399)	(0.2141)
government	0.0082	0.0275	0.0098	0.0342
	(0.0289)	(0.0217)	(0.0327)	(0.0233)
		external		
mean current account deficit	$\mathbf{-0.2280}^*$	$\mathbf{-0.1420}^*$	$\mathbf{-0.1744}^*$	$\mathbf{-0.1271}^*$
	(0.0473)	(0.0314)	(0.0529)	(0.0344)
$\sigma^2_{\text{mean CAD}}$	0.0402	0.0188	0.0490	0.0197
	(0.0159)	(0.0050)	(0.0222)	(0.0052)
openness	-0.0047	-0.0027	0.0016	-0.0023
	(0.0059)	(0.0038)	(0.0067)	(0.0040)
reserves	$\mathbf{-0.2965}^*$	$\mathbf{-0.1541}^*$	$\mathbf{-0.3487}^*$	$\mathbf{-0.2640}^*$
	(0.0991)	(0.0594)	(0.1084)	(0.0709)
$\sigma^2_{\text{reserves}}$	0.0978	0.0262	0.1143	0.0262
	(0.0555)	(0.0089)	(0.0581)	(0.0089)
official transfers	$\mathbf{-0.0766}^*$	$\mathbf{-0.0966}^*$	-0.0502	$\mathbf{-0.0701}$
	(0.0431)	(0.0449)	(0.0436)	(0.0475)
$\sigma^2_{\text{official transfers}}$	0.0257	0.0193	0.0271	0.0201
	(0.0078)	(0.0051)	(0.0088)	(0.0056)
concessional debt	-0.0033	-0.0045	-0.0065	-0.0145
	(0.0117)	(0.0076)	(0.0144)	(0.0098)
interest payments	0.0992	0.0165	$\mathbf{0.1853}^*$	0.0716
	(0.0579)	(0.0512)	(0.0730)	(0.0626)
terms of trade	$\mathbf{-0.0137}^*$	$\mathbf{-0.0092}^*$	$\mathbf{-0.0124}^*$	$\mathbf{-0.0091}^*$
	(0.0050)	(0.0035)	(0.0056)	(0.0038)
		global		
US real interest rate	**0.1163**	0.0865	-0.0166	0.0189
	(0.0838)	(0.0711)	(0.0959)	(0.0793)
OECD growth rate	0.1502	0.1531	0.0592	0.0362
	(0.1005)	(0.1002)	(0.1189)	(0.1146)
ρ	$\mathbf{0.5984}^*$	$\mathbf{-0.3664}^*$	$\mathbf{0.6154}^*$	$\mathbf{-0.3655}$
	(0.0871)	(0.1723)	(0.0976)	(0.1946)
log(marg-lik)	-327.1516	-292.0472	-234.9933	-224.4384

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.11: Probit model with partial heterogeneity and serial correlation (parsimonious) - Bayesian estimates

	I	*II*	*III*	*IV*
constant	−0.3336 (0.8251)	−0.7587 (0.5185)	−1.5751 (1.0557)	−0.9577 (0.6122)
		external		
mean current account deficit	**−0.2313*** (0.0459)	**−0.1458*** (0.0318)	**−0.1868*** (0.0527)	**−0.1237*** (0.0349)
$\sigma^2_{\text{mean CAD}}$	0.0418 (0.0184)	0.0180 (0.0047)	0.0501 (0.0226)	0.0193 (0.0053)
openness	−0.0021 (0.0054)	−0.0007 (0.0031)	0.0056 (0.0058)	0.0015 (0.0033)
reserves	**−0.3216*** (0.0975)	**−0.1712*** (0.0618)	**−0.3417*** (0.1061)	**−0.2452*** (0.0755)
$\sigma^2_{\text{reserves}}$	0.1056 (0.0596)	0.0243 (0.0074)	0.1160 (0.0581)	0.0249 (0.0079)
official transfers	**−0.0865*** (0.0395)	**−0.0982*** (0.0353)	**−0.0670*** (0.0429)	**−0.0814*** (0.0378)
$\sigma^2_{\text{official transfers}}$	0.0262 (0.0086)	0.0190 (0.0050)	0.0268 (0.0087)	0.0198 (0.0053)
concessional debt	−0.0113 (0.0100)	−0.0091 (0.0060)	−0.0097 (0.0124)	**−0.0144** (0.0078)
interest payments	0.0879 (0.0560)	0.0180 (0.0486)	**0.1494*** (0.0678)	0.0561 (0.0592)
terms of trade	**−0.0122*** (0.0052)	**−0.0077*** (0.0033)	**−0.0122*** (0.0059)	**−0.0085*** (0.0039)
ρ	**0.6100** (0.0904)	**−0.3355*** (0.1675)	**0.6123*** (0.0988)	**−0.3665** (0.2069)
log(marg-lik)	-291.6727	-268.2328	-203.1616	-198.9042

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Tab. 2.12: Classification analysis for reversals with Bayesian probit estimates

		I			*II*			*III*			*IV*		
		0	1	$\sum$	0	1	$\sum$	0	1	$\sum$	0	1	$\sum$
pooled	0	848	15	863	903	0	903	890	6	896	921	1	922
	1	90	10	100	59	1	60	65	2	67	40	1	41
	$\sum$	938	25	963	962	1	963	955	8	963	961	2	963
		0	1	$\sum$	0	1	$\sum$	0	1	$\sum$	0	1	$\sum$
serial	0	856	7	863	903	0	903	891	5	896	922	0	922
	1	81	19	100	59	1	60	52	15	67	41	0	41
	$\sum$	937	26	963	962	1	963	943	20	963	963	0	963
		0	1	$\sum$	0	1	$\sum$	0	1	$\sum$	0	1	$\sum$
heterogeneity	0	856	7	863	903	0	903	892	4	896	921	1	922
	1	71	29	100	56	4	60	45	22	67	36	5	41
	$\sum$	927	36	963	959	4	963	937	26	963	957	6	963
		0	1	$\sum$	0	1	$\sum$	0	1	$\sum$	0	1	$\sum$
het.+serial	0	856	7	863	903	0	903	889	7	896	921	1	922
	1	76	24	100	56	4	60	39	28	67	36	5	41
	$\sum$	932	31	963	959	4	963	927	35	963	957	6	963

Notes: The columns refer to the identified state, whereas the rows give the observed state.

Tab. 2.13: Pooled treatment model - Bayesian estimates

	I	*II*	*III*	*IV*
σ	4.9960 (0.1393)	4.9527 (0.1301)	4.7916 (0.1184)	4.7849 (0.1162)
ψ/σ	**0.6590*** (0.0724)	**0.6851*** (0.0893)	**0.4079*** (0.1123)	**0.4162*** (0.1404)
constant	**1.7255** (1.0732)	1.6683 (1.0695)	1.7096 (1.0528)	**1.7853** (1.0459)
lagged growth rate	**0.1611*** (0.0324)	**0.1603*** (0.032)	**0.1656*** (0.0315)	**0.1653*** (0.0319)
reversal	−**6.9888*** (1.1753)	−**7.0228*** (1.4288)	−**5.7425*** (1.6464)	−**4.6573*** (1.9739)
reversal × openness	0.0101 (0.0121)	−0.0038 (0.0145)	0.0181 (0.0145)	−0.0031 (0.0171)
openness	**0.0089** (0.0050)	**0.0086** (0.0048)	**0.0095*** (0.0047)	**0.0095*** (0.0047)
mean investment	**0.0694*** (0.0236)	**0.0713*** (0.0232)	**0.0676*** (0.0227)	**0.0632*** (0.0225)
initial log GDP	−0.0415 (0.1502)	−0.0645 (0.1475)	−0.0951 (0.1465)	−0.1049 (0.1451)
constant	−**2.6534*** (0.7592)	−**2.2508*** (0.8648)	−**2.1011*** (0.8903)	−1.5821 (1.0588)
	macroeconomic			
mean growth rate	**0.0321** (0.0187)	0.0243 (0.0211)	**0.0427** (0.0238)	0.0273 (0.0273)
mean investment	0.0023 (0.0098)	0.0067 (0.0115)	0.0139 (0.0117)	0.0121 (0.0136)
log initial GDP	0.0822 (0.0779)	0.0572 (0.0849)	0.0302 (0.0938)	0.0025 (0.1082)
government	0.0128 (0.0112)	0.0005 (0.0127)	**0.0292*** (0.0130)	0.0159 (0.0147)
	external			
mean current account deficit	−**0.0677*** (0.0113)	−**0.0591*** (0.0127)	−**0.0604*** (0.0131)	−**0.0529*** (0.0151)
openness	−0.0016 (0.0021)	−0.0018 (0.0023)	0.0002 (0.0024)	−0.0004 (0.0027)
reserves	−**0.0884*** (0.0263)	−**0.0740*** (0.0289)	−**0.1246*** (0.0383)	−**0.1365*** (0.0479)
official transfers	−**0.0356*** (0.0115)	−**0.0357*** (0.0131)	−0.0116 (0.0135)	−0.0089 (0.0156)
concessional debt	−0.0054 (0.0037)	−**0.0073*** (0.0041)	−**0.0143*** (0.0054)	−**0.0187*** (0.0064)
interest payments	0.0104 (0.0273)	−0.0092 (0.0297)	0.0454 (0.0333)	0.0126 (0.0353)
terms of trade	−0.0022 (0.0015)	−0.0023 (0.0018)	−**0.0067*** (0.0023)	−**0.0055*** (0.0025)
	global			
US real interest rate	**0.1103*** (0.0449)	0.0712 (0.0510)	0.0501 (0.056)	0.0324 (0.0655)
OECD growth rate	**0.1276*** (0.0619)	**0.1223** (0.0724)	0.0846 (0.0803)	0.0858 (0.0873)
log(marg.-lik.)	-3280.0	-3207.6	-3199.2	-3146.8

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.14: Treatment model with serial correlation- Bayesian estimates

	I	*II*	*III*	*IV*
σ	4.8833 (0.1310)	4.8753 (0.1251)	4.7669 (0.1133)	4.7718 (0.1145)
ψ/σ	**0.5275*** (0.0927)	**0.5673*** (0.0966)	**0.3221*** (0.1148)	**0.3610*** (0.1506)
ρ	**0.0974*** (0.0486)	−0.0712 (0.0515)	**0.0785** (0.0474)	−0.0262 (0.0488)
constant	**1.7935** (1.0611)	**1.7186** (1.0377)	**1.7993** (1.0389)	**1.7955** (1.0382)
lagged growth rate	**0.1635*** (0.0321)	**0.1614*** (0.0327)	**0.1657*** (0.0319)	**0.1659*** (0.0315)
reversal	**−5.7542*** (1.3021)	**−5.9554*** (1.5105)	**−5.0010*** (1.6737)	**−4.2330*** (2.0123)
reversal × openness	0.0100 (0.0125)	−0.0037 (0.0148)	0.0169 (0.0148)	−0.0035 (0.0170)
openness	**0.0085** (0.0048)	**0.0087** (0.0048)	**0.0091*** (0.0046)	**0.0096*** (0.0048)
mean investment	**0.0661*** (0.0230)	**0.0684*** (0.0232)	**0.0658*** (0.0224)	**0.0627*** (0.0225)
initial log GDP	−0.0579 (0.1480)	−0.0755 (0.1451)	−0.1054 (0.1445)	−0.1083 (0.1444)
constant	**−2.8188*** (0.8316)	**−2.1998*** (0.8488)	**−2.1046*** (0.9817)	−1.4697 (1.0248)
		macroeconomic		
mean growth rate	0.0263 (0.0210)	0.0175 (0.0221)	0.0412 (0.0249)	0.0269 (0.0274)
mean investment	0.0038 (0.0115)	0.0070 (0.0110)	0.0139 (0.0128)	0.0115 (0.0137)
log initial GDP	0.1035 (0.0861)	0.0362 (0.0880)	0.0445 (0.1046)	−0.0038 (0.1061)
government	0.0167 (0.0117)	0.0034 (0.0129)	0.0282 (0.0132)	0.0183 (0.0149)
		external		
mean current account deficit	**−0.0714*** (0.0124)	**−0.0588** (0.0127)	**−0.0628*** (0.0136)	**−0.0525*** (0.0150)
openness	−0.0025 (0.0024)	−0.0015 (0.0023)	−0.0005 (0.0026)	−0.0004 (0.0026)
reserves	**−0.0987*** (0.0310)	**−0.0721*** (0.0310)	**−0.1385*** (0.0434)	**−0.1375*** (0.0446)
official transfers	−0.0306 (0.0114)	**−0.0353*** (0.0136)	−0.0073 (0.0138)	−0.0080 (0.0163)
concessional debt	−0.0055 (0.0040)	**−0.0079** (0.0042)	**−0.0144*** (0.0055)	**−0.0196*** (0.0063)
interest payments	0.0147 (0.0293)	−0.0045 (0.0306)	0.0470 (0.0344)	0.0125 (0.0361)
terms of trade	**−0.0029*** (0.0017)	−0.0025 (0.0019)	**−0.0074*** (0.0024)	**−0.0055*** (0.0025)
		global		
US real interest	**0.1166*** (0.0498)	**0.0750** (0.0531)	0.0527 (0.0612)	0.0222 (0.0638)
OECD growth	**0.1230*** (0.0668)	**0.1217** (0.0753)	0.0817 (0.0833)	0.0772 (0.0933)
log(marg.-lik.)	-3277.2	-3207.9	-3197.5	-3150.9

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.15: Treatment model with serial correlation and heterogeneity - Bayesian estimates

	I	*II*	*III*	*IV*
σ	4.5420	4.5919	4.5323	4.5434
	(0.1123)	(0.1266)	(0.1106)	(0.1129)
ψ/σ	0.1126	0.3861	0.0379	0.1514
	(0.1538)	(0.2466)	(0.1249)	(0.1972)
ρ	0.0562	−0.0293	0.0432	−0.0136
	(0.0460)	(0.0490)	(0.0473)	(0.0469)
constant	**2.1834**	**2.0265**	**2.1553**	**2.0911**
	(1.1334)	(1.1457)	(1.1079)	(1.1238)
$\sigma^2_{\text{constant}}$	0.0494	0.0505	0.0505	0.0516
	(0.0263)	(0.0271)	(0.0266)	(0.0311)
lagged growth rate	**0.2176***	**0.2135***	**0.2190***	**0.2177***
	(0.0436)	(0.0444)	(0.0438)	(0.0438)
$\sigma^2_{\text{lagged growth}}$	0.0401	0.0409	0.0400	0.0399
	(0.0110)	(0.0110)	(0.0109)	(0.0109)
reversal	−2.0890	−3.8804	−2.6211	−2.4797
	(1.4380)	(2.3037)	(1.5769)	(2.1991)
reversal × openness	0.0064	−0.0046	0.0145	−0.0015
	(0.0132)	(0.0156)	(0.0154)	(0.0181)
openness	**0.0092**	**0.0102**	**0.0094**	**0.0105***
	(0.0052)	(0.0052)	(0.0052)	(0.0052)
mean investment	0.0205	0.0233	0.0215	0.0206
	(0.0241)	(0.0243)	(0.0245)	(0.0241)
initial log GDP	−0.0775	−0.0569	−0.0894	−0.0850
	(0.1584)	(0.1625)	(0.1549)	(0.1590)
constant	−0.1828	−0.3730	−0.4765	−0.6061
	(0.5947)	(0.5999)	(0.7283)	(0.6680)
	external			
mean current account deficit	**−0.2155***	**−0.1522***	**−0.2067***	**−0.1448***
	(0.0378)	(0.0362)	(0.0429)	(0.0375)
$\sigma^2_{\text{mean CAD}}$	0.0248	0.0201	0.0274	0.0224
	(0.0071)	(0.0054)	(0.0086)	(0.0067)
openness	−0.0039	−0.0009	0.0004	0.0007
	(0.0033)	(0.0033)	(0.0037)	(0.0036)
reserves	**−0.2598***	**−0.2452***	**−0.3757***	**−0.3564***
	(0.0873)	(0.0798)	(0.1125)	(0.1013)
$\sigma^2_{\text{reserves}}$	0.0382	0.0340	0.0530	0.0399
	(0.0162)	(0.0135)	(0.0268)	(0.0175)
official transfers	**−0.1156***	**−0.1304***	**−0.1548***	**−0.1469***
	(0.0424)	(0.0433)	(0.0648)	(0.0505)
$\sigma^2_{\text{official transfers}}$	0.0262	0.0250	0.0329	0.0287
	(0.0084)	(0.0080)	(0.0118)	(0.0092)
concessional debt	−0.0086	−0.0112	−0.0070	−0.0159
	(0.0065)	(0.0071)	(0.0094)	(0.0091)
interest payments	0.0675	0.0049	**0.1405***	0.0533
	(0.0460)	(0.0512)	(0.0578)	(0.0605)
terms of trade	**−0.0102***	**−0.0080***	**−0.0147***	**−0.0088***
	(0.0038)	(0.0034)	(0.0047)	(0.0044)
log(marg.-lik.)	-3224.8	-3177.2	-3127.6	-3095.2

Notes: Bayesian estimates are given as the means of the posterior distributions. Standard errors are given in parentheses. Bold figures indicate that the 90% highest density region does not include zero. Bold figures with * indicate that the 95% highest density region does not include zero.

Tab. 2.16: Log marginal likelihoods

probit	*I*	*II*	*III*	*IV*
pooled	-381.3095	-308.7889	-295.4025	-244.0496
serial	-357.0324	-307.3159	-262.4228	-244.2613
heterogeneity	-352.6263	-300.7738	-258.3797	-229.1459
serial & heterogeneity	-327.1516	-292.0472	-234.9933	-224.4384
serial & heterogeneity (parsimonious)	-291.6727	-268.2328	-203.1616	-198.9042
treatment	*I*	*II*	*III*	*IV*
pooled	-3280.0	-3207.6	-3199.2	-3146.8
serial	-3277.2	-3207.9	-3197.5	-3150.9
serial & heterogeneity	-3253.2	-3204.8	-3164.1	-3121.9
serial & heterogeneity, prior •	-3254.9	-3205.3	-3152.3	-3130.6
serial & heterogeneity, prior ••	-3225.2	-3178.6	-3101.4	-3108.4
serial & heterogeneity (parsimonious)	-3224.8	-3177.2	-3127.6	-3095.2

Tab. 2.17: Convergence diagnostic

	probit model	treatment model
parameter	CD-statistic	CD-statistic
probit equation		
constant	-1.1326	1.2335
mean growth rate	-0.3080	1.0878
mean investment	0.7892	2.3429
initial log GDP	0.6077	-1.5826
government	-0.1786	-0.1199
mean current account deficit	0.6590	-0.6579
$\sigma^2_{\text{mean CAD}}$	-1.0333	-1.0738
openness	1.3708	-0.1694
reserves	0.9210	-0.2588
$\sigma^2_{\text{reserves}}$	2.4381	1.6846
official transfers	0.0127	-0.4481
$\sigma^2_{\text{official transfers}}$	0.7956	-1.1189
concessional debt	1.3585	-1.6714
interest payments	-0.5103	1.1786
terms of trade	0.0147	-0.2515
US real interest rate	-1.6652	-0.3992
OECD growth rate	-0.3736	0.5496
ρ	0.4815	-1.4618
ψ	–	0.9371
σ^2	–	0.7026
growth equation		
constant	–	0.3900
$\sigma^2_{\text{constant}}$	–	-1.3075
lagged growth rate	–	0.4898
$\sigma^2_{\text{lagged growth}}$	–	0.2294
reversal	–	-0.4879
reversal × openness	–	0.2272
openness	–	0.3903
mean investment	–	1.0708
initial log GDP	–	-0.4413

Notes: The CD-statistic tests for the equality of the sample mean at the beginning and end of the sampled sequence with

$$CD = \frac{\overline{x}_A - \overline{x}_B}{\sqrt{\frac{S_A^2}{n_A} + \frac{S_B^2}{n_B}}} \overset{\text{asy}}{\sim} \mathcal{N}(0,1),$$

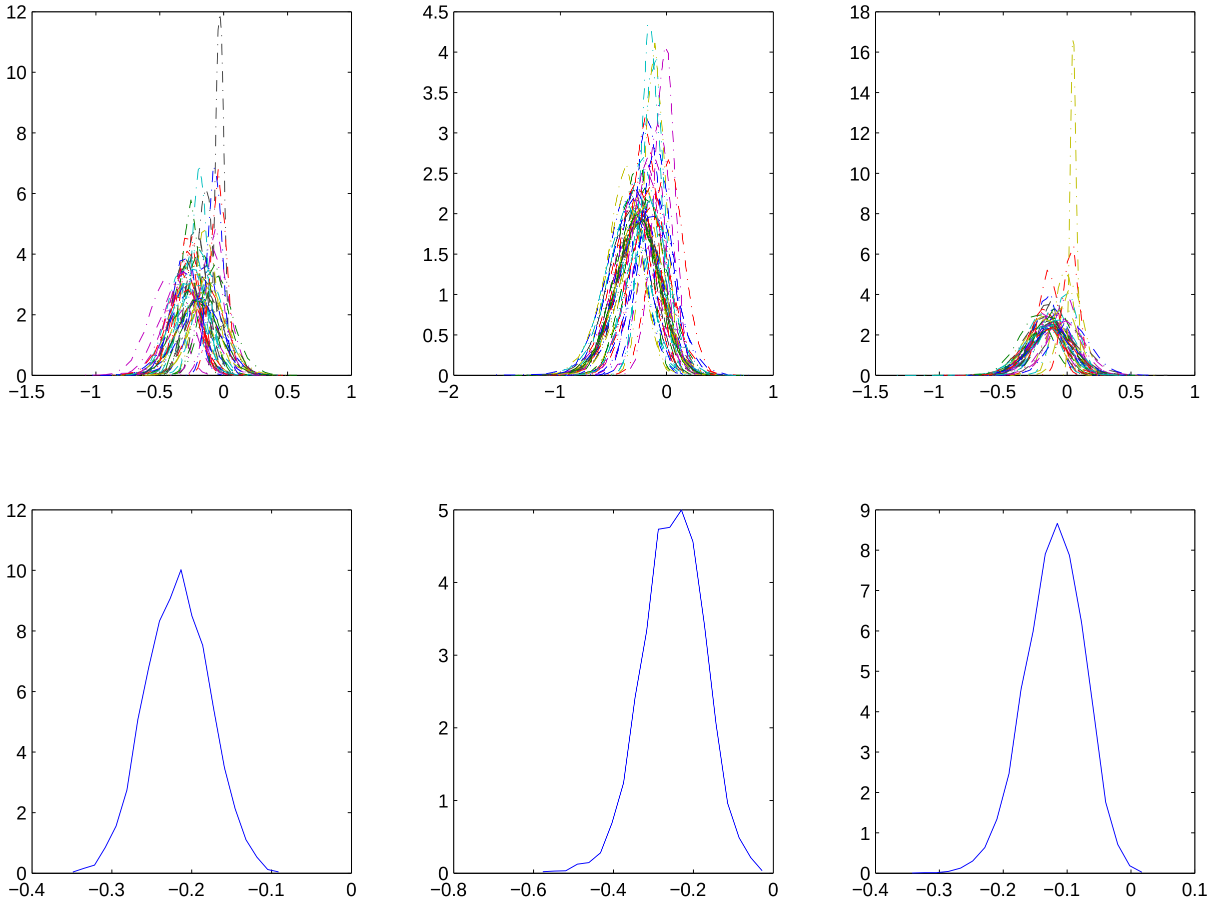
where A refers to the first 10% and B to the last 50% of the Gibbs sequence. The variance is estimated according to the Newey-West, see Newey and West (1987) robust estimator as the numerical equivalent to 2π times the spectral density estimator at frequency zero used in Geweke (1992).

Tab. 2.18: Cumulated costs of reversals

	pooled specification							
	reversal scheme I		reversal scheme II		reversal scheme III		reversal scheme IV	
	Loss	95% CI	Loss	95% CI	Loss	95% CI	Loss	95%CI
$t = 0$	-1.9386	$[-3.1222\ ;\ -0.6318]$	-2.0239	$[-3.2737\ ;\ -0.7954]$	-1.5244	$[-2.7405\ ;\ -0.3252]$	-1.5151	$[-2.8765\ ;\ -0.1491]$
$t = 1$	-1.2990	$[-2.5595\ ;\ -0.0158]$	-0.9637	$[-2.1903\ ;\ 0.2501]$	-0.7280	$[-1.9921\ ;\ 0.6327]$	-0.5862	$[-1.8671\ ;\ 0.7524]$
$t = 2$	-0.8645	$[-2.1199\ ;\ 0.4765]$	-0.5417	$[-1.7913\ ;\ 0.6992]$	-0.3655	$[-1.6231\ ;\ 0.8367]$	-0.2882	$[-1.6049\ ;\ 0.9270]$
$t = 3$	-0.5440	$[-1.8268\ ;\ 0.7802]$	-0.3574	$[-1.6268\ ;\ 0.9533]$	-0.2232	$[-1.6401\ ;\ 1.0884]$	-0.1651	$[-1.4629\ ;\ 1.1796]$
$\sum$	-4.6461	$[-7.3960\ ;\ -1.7842]$	-3.8868	$[-6.6005\ ;\ -1.0604]$	-2.8412	$[-5.7935\ ;\ -0.0265]$	-2.5546	$[-5.5054\ ;\ 0.4248]$
	specification with heterogeneity and serial correlation							
	reversal scheme I		reversal scheme II		reversal scheme III		reversal scheme IV	
	Loss	95% CI	Loss	95% CI	Loss	95% CI	Loss	95%CI
$t = 0$	-0.8511	$[-2.1220\ ;\ 0.3596]$	-0.8524	$[-2.0893\ ;\ 0.2723]$	-1.1873	$[-2.4115\ ;\ 0.0436]$	-1.1956	$[-2.5950\ ;\ 0.1640]$
$t = 1$	-0.1537	$[-1.4028\ ;\ 1.1189]$	-0.2962	$[-1.5882\ ;\ 0.9916]$	-0.2741	$[-1.5394\ ;\ 1.0335]$	-0.3210	$[-1.6514\ ;\ 1.0344]$
$t = 2$	-0.0138	$[-1.3134\ ;\ 1.2329]$	-0.1305	$[-1.4711\ ;\ 1.1968]$	-0.0099	$[-1.2992\ ;\ 1.2720]$	-0.1112	$[-1.3488\ ;\ 1.2250]$
$t = 3$	-0.0522	$[-1.2835\ ;\ 1.1357]$	-0.1492	$[-1.5469\ ;\ 1.1894]$	-0.0431	$[-1.3043\ ;\ 1.2203]$	-0.1582	$[-1.4745\ ;\ 1.2726]$
$\sum$	-1.0708	$[-3.9263\ ;\ 1.6410]$	-1.4284	$[-4.4972\ ;\ 1.5940]$	-1.5144	$[-4.5614\ ;\ 1.3605]$	-1.7861	$[-4.7999\ ;\ 1.3226]$

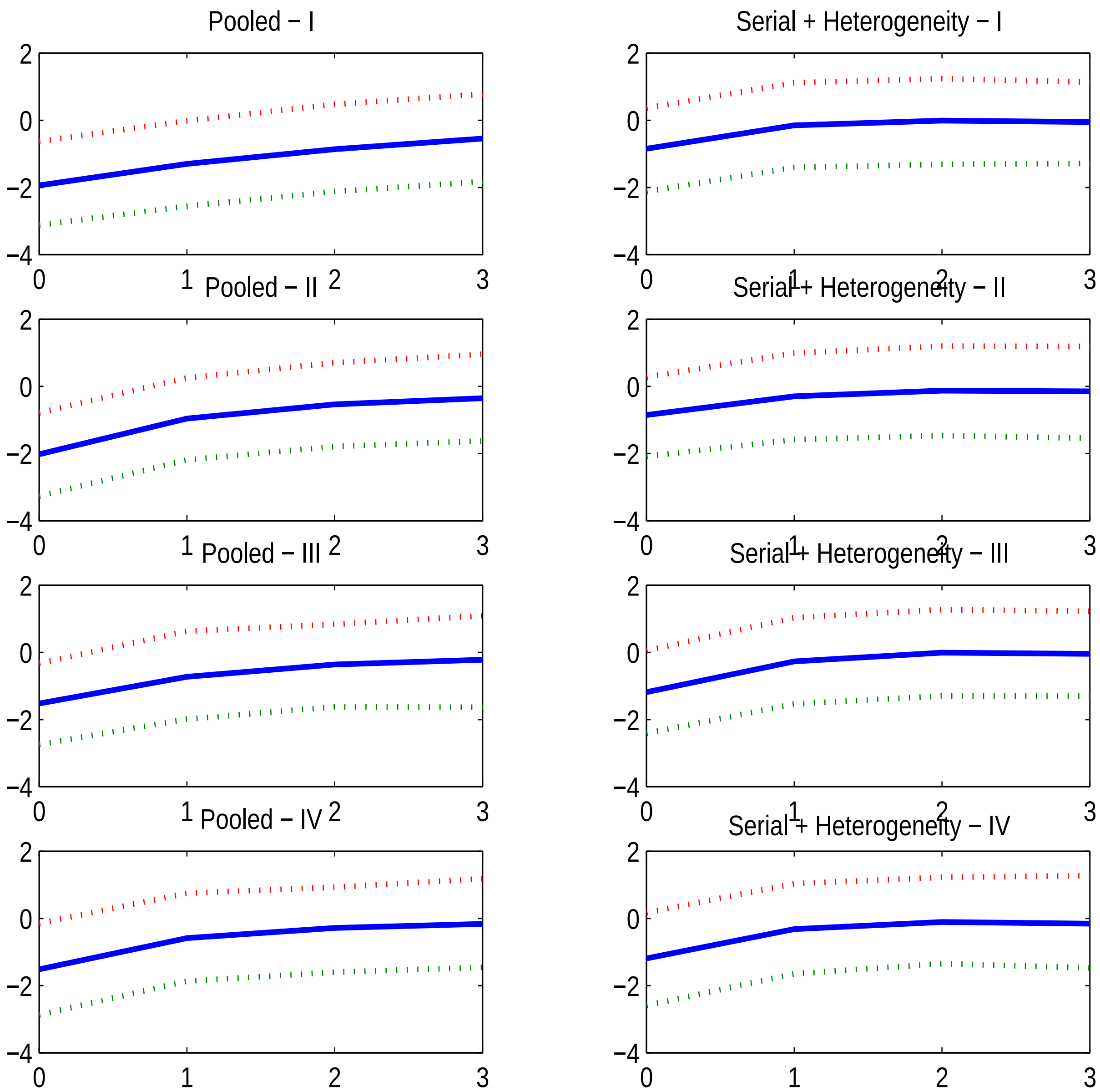
Notes: Table refers to pooled specification of treatment model (upper panel) and specification incorporating serial correlation and heterogeneity (lower panel); results are based on 1000 replications.

Fig. 2.1: Heterogeneity within the probit coefficients



Notes: Heterogeneity for reversal scheme I: left - histograms of the sampled country specific coefficient for variable mean current account deficit; middle - histograms of the sampled country specific coefficient for variable reserves; right - histograms of the sampled country specific coefficient for variable official transfers; The upper panel shows all countries; the lower panel shows the histogram of the average over all countries of the sampled coefficients.

Fig. 2.2: Reversal costs over time



Notes: dotted lines indicate 95% bands; solid lines give mean response to reversal shock

2.7 Technical Details

Bayesian inference is concerned about the posterior distribution $p(\theta|Y)$ and corresponding moments.[30] Gibbs sampling is a device to produce a sample from the posterior distribution, which can be used to calculate posterior moments and density estimates. Posterior draws of θ partitioned into convenient blocks $\theta = \{\theta_1, \ldots, \theta_K\}$ are obtained via Gibbs sampling, when direct sampling from the posterior distribution is difficult, but sampling from the full conditional distributions is directly accessible. The functional form of the full conditional distributions can be deduced from the joint distribution of parameters θ and sample data S

$$p(\theta, S) = L(S|\theta)\pi(\theta)$$

via isolating the kernel of a single block conditional on all other blocks and the data

$$p(\theta_k|\theta_1, \ldots, \theta_{k-1}, \theta_{k+1}, \ldots, \theta_K, S).$$

Given an initialization θ_0 the Gibbs sampling algorithm simulates iteratively for $r = 1, \ldots, R$ from the full conditional distributions

$$\begin{aligned}
&p(\theta_1|\theta_2^{(r-1)}, \ldots, \theta_K^{(r-1)}, S),\\
&p(\theta_2|\theta_1^{(r)}, \theta_3^{(r-1)}, \ldots, \theta_K^{(r-1)}, S),\\
&\vdots\\
&p(\theta_K|\theta_1^{(r)}, \ldots, \theta_{K-1}^{(r)}, S).
\end{aligned}$$

The iterative sampling constitutes a Markov chain, which ensures under general regularity conditions given in Chib (2001) convergence to the joint posterior distribution.[31]Since these are

[30] A general introduction in the basic principles employed in the following Bayesian analysis is provided by Geweke (1999) and Koop (2003).

[31] Following Chib (2001), the transition from $\theta_k^{(r)}$ to $\theta_k^{(r+1)}$ is accomplished via sampling from $p(\theta_k|\theta_1^{(r)}, \ldots, \theta_{k-1}^{r}, \theta_{k+1}^{(r-1)}, \ldots, \theta_K^{(r-1)}, S)$. The transition of the Markov chain constituting out of K blocks is then described for continuous full conditional distributions as

$$K(\theta^r, \theta^{r+1}) = \prod_{k=1}^{K} p(\theta_k|\theta_1^{(r)}, \ldots, \theta_{k-1}^{r}, \theta_{k+1}^{(r-1)}, \ldots, \theta_K^{(r-1)}, S).$$

Sufficient conditions for convergence can then be stated as follows. Let $K(\theta, \theta')$ denote the transition density of the Gibbs sampler and let $K^R(\theta_o, \theta')$ be the density of θ' after R iterations of the Gibbs sampler given the initialization θ_0. The

$$\|K^R(\theta_o, \theta') - p(\theta|S)\| \to 0 \text{ as } R \to \infty,$$

where $\| \cdot \|$ denotes the total variance distance. As it is shown by Robert and Smiwth (1994), convergence is ensured under the following conditions

1. $p(\theta|S) > 0$ implies there exists an open neighborhood N_θ containing θ and $\xi > 0$ such that, for all $\theta' \in N_\theta$, $p(\theta_\prime) \geq \xi > 0$;
2. $\int f(\theta) d\theta_k$ is locally bounded for all k, where θ_k is the kth block of parameters;
3. the support of θ is arc connected,

where these conditions are not met only for pathological cases.

fulfilled in the context of the considered probit and treatment regressions the convergence of the joint distribution of the sample $\theta^{(R)}$ for $R \to \infty$ towards the posterior distribution

$$p(\theta|S) = \frac{p(\theta, S)}{m(S)}$$

where $m(S)$ is the corresponding unknown integrating constant denoted as the marginal likelihood. Since the functional form of the full conditional distributions depend on the functional forms of the prior distributions, these are in general conveniently chosen chosen to allow direct sampling from the full conditional distributions.

Data augmentation as introduced by Tanner and Wong (1987) includes latent variables of the model into the parameter vector, e.g. in the considered pooled probit model the parameter vector $\theta = \beta$ is augmented to include all latent variables δ^*. The joint posterior distribution $p(\beta, \delta^*|S)$ is then subject to analysis via Gibbs sampling. While this augmentation complicates the matter of sampling directly from the full conditional distribution it is most often applied when it simplifies sampling from the full conditional distributions. In the present context of probit and treatment models, augmenting the parameter vector by the latent variable δ^* provides a linearization scheme of the nonlinear modelsetup and results in a linear regression setup with normal errors, which allows to determine the full conditional distributions for the structural parameters of interest.

The functional forms of the full conditional distributions employed within the Gibbs sampling schemes are provided for the Probit and Treatment model with serially correlated errors and partial random coefficients in the following Subsections 2.7.1 and 2.7.2. Subsection 2.7.3 provides furthermore the functional forms of the employed distributions and the hyperparameters of the prior distributions and shortly discusses the related informational content assigned a priori to parameters.

2.7.1 *Probit Model with Serial Correlation and partial Heterogeneity via Random Coefficients*

The probit model with serially correlated errors and partially assigned random coefficients is outlined in Equations (2.1)-(2.9). Gibbs sampling for this model specification builds upon the set of full conditional distributions for $\{\beta_i\}_{i=1}^N$, b, W_b, ρ, $\{\{e_{it}\}_{t=S(i)}^{T(i)}\}_{i=1}^N$ and $\overline{\beta}$. In the following the parameters and moments of each full conditional distribution are explicitly given. Define

$$\Sigma_i = \begin{pmatrix} \frac{1}{1-\rho^2} & \frac{\rho}{1-\rho^2} & \cdots & \frac{\rho^{T(i)-S(i)}}{1-\rho^2} \\ \frac{\rho}{1-\rho^2} & \frac{1}{1-\rho^2} & & \vdots \\ \vdots & & \ddots & \\ \frac{\rho^{T(i)-S(i)}}{1-\rho^2} & \cdots & & \frac{1}{1-\rho^2} \end{pmatrix}$$

as the covariance matrix of the error vector $e_{i\cdot}$. The full conditional distributions are given as follows

(i) For each individual i define

$$\xi_{i\cdot} = \delta^*_{i\cdot} - \overline{X}_{i\cdot}\overline{\beta},$$

hence the vector of random coefficients is drawn from a multivariate normal distribution $\mathcal{N}(\mu_{\beta_i}, \Sigma_{\beta_i})$, where

$$\begin{aligned}\mu_{\beta_i} &= \left(X_{i\cdot}^{\text{ran}\prime}\Sigma_i^{-1}X_{i\cdot}^{\text{ran}} + W_b^{-1}\right)^{-1}\left(X_{i\cdot}^{\text{ran}\prime}\Sigma_i^{-1}\xi_{i\cdot} + W_b^{-1}b\right)\\ \Sigma_{\beta_i} &= \left(X_{i\cdot}^{\text{ran}\prime}\Sigma_i^{-1}X_{i\cdot}^{\text{ran}} + W_b^{-1}\right)^{-1}.\end{aligned}$$

(ii) The mean parameter b is sampled conditional on the country specific random coefficients $\{\beta_i\}_{i=1}^N$ from a multivariate normal distribution $\mathcal{N}(\mu_b, \Sigma_b)$, when a normal prior (μ_{b0}, Ω_{b0}) is assumed. Hence

$$\mu_b = \left(NW_b^{-1} + \Omega_{b0}^{-1}\right)^{-1}\left(NW_b^{-1}\left(\frac{1}{N}\sum_{i=1}^N \beta_i\right) + \Omega_{b0}^{-1}\mu_{b0}\right), \quad \Sigma_b = \left(NW_b^{-1} + \Omega_{b0}^{-1}\right)^{-1}.$$

(iii) The covariance matrix of the random coefficients can either be diagonal or allowing for correlation between the parameters. In case of a diagonal matrix with n^{ran} denoting the number of random coefficients, the diagonal elements W_b^{jj}, $j = 1, \ldots, n^{\text{ran}}$ are sampled, when a conjugate inverse gamma prior $\mathcal{IG}(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})$ is used, from independent inverse gamma distributions $\mathcal{IG}(\alpha_{W_b^{jj}}, \beta_{W_b^{jj}})$, where

$$\alpha_{W_b^{jj}} = \frac{N}{2} + \alpha_{W_b^{jj}0}, \quad \beta_{W_b^{jj}} = \frac{1}{2}\sum_{i=1}^N (\beta_i^{jj} - b^{jj})^2 + \beta_{W_b^{jj}0}.$$

In case of a full specified matrix, W_b is sampled from an inverted Wishart distribution $\mathcal{IW}(q_{W_b}, S_{W_b})$ with an inverted Wishart $\mathcal{IW}(q_{W_b0}, S_{W_b0})$ as the prior distribution. Thus

$$\begin{aligned}q_{W_b} &= q_{W_b0} + N,\\ S_{W_b} &= q_{W_b0}S_{W_b0} + \left(\sum_{i=1}^N (\beta_i - b)(\beta_i - b)'\right).\end{aligned}$$

(iv) The serial correlation parameter ρ is obtained via setting up the regression of the residuals e_{it} on their lagged counterparts. Define

$$\zeta_i^1 = (e_{iS(i)}, \ldots, e_{iT(i)-1})', \quad \zeta_i^2 = (e_{iS(i)+1}, \ldots, e_{iT(i)})'.$$

Hence, given a uniform prior, ρ is sampled from a truncated normal distribution $\mathcal{N}_{\mathcal{T}_\rho}(\mu_\rho, \sigma_\rho^2)$, where

$$\mu_\rho = (\zeta_i^{1\prime}\zeta_i^1)^{-1}(\zeta_i^{1\prime}\zeta_i^2), \quad \sigma_\rho^2 = (\zeta_i^{1\prime}\zeta_i^1)^{-1}, \quad \mathcal{T}_\rho = (-1, 1).$$

(v) The Bayesian estimation approach allows to linearize the model via inclusion of the latent dependent variable δ_{it}^* within the augmented parameter vector. The latent dependent $\delta_{i\cdot}^*$ is obtained via the calculation of

$$\delta_{it}^* = \overline{X}_{i\cdot}'\overline{\beta} + X_{i\cdot}^{\text{ran}\prime}\beta_i + e_{it}.$$

The latent errors are therefore sampled from a multivariate truncated normal distribution $\mathcal{N}_{\mathcal{T}_{e_{i\cdot}}}(\mu_{e_{i\cdot}}, \Sigma_{e_{i\cdot}})$, where

$$\begin{aligned}
\mu_{e_{i\cdot}} &= 0 \\
\Sigma_{e_{i\cdot}} &= \Sigma_i, \\
\mathcal{T}_{e_{i\cdot}} &= (\sqcup_{S(i)}, \ldots, \sqcup_{T(i)})', \\
\sqcup_t &= \begin{cases} (-(\overline{X}'_{it}\overline{\beta} + X^{\mathrm{ran}\prime}_{it}\beta_i), \infty), & \text{if } \delta_{it} = 1 \\ (-\infty, -(\overline{X}'_{it}\overline{\beta} + X^{\mathrm{ran}\prime}_{it}\beta_i)), & \text{if } \delta_{it} = 0 \end{cases}, \quad t = S(i), \ldots, T(i).
\end{aligned}$$

As draws from a multivariate truncated normal distribution cannot be obtained from a closed form density, the algorithm of Geweke (1991) is employed. Each element of $e_{i\cdot}$ is drawn conditional on all other elements from a univariate truncated normal distribution. Denote $I_{k\times k}$ as identity matrix and $O_{k\times k}$ as a matrix containing only zeros. Hence, define for $t = 1, \ldots, T(i) - S(i) + 1$

$$M_{i/t} = \begin{pmatrix} I_{t-1\times t-1} & O_{t-1\times 1} & O_{t-1\times 1} & O_{t-1\times T(i)-S(i)-t} \\ O_{1\times t-1} & 0 & 1 & O_{1\times T(i)-S(i)-t} \\ O_{T(i)-S(i)-t\times t-1} & O_{T(i)-S(i)-t\times 1} & O_{T(i)-S(i)-t\times 1} & I_{T(i)-S(i)-t\times T(i)-S(i)-t} \end{pmatrix}$$

and

$$\overline{M}_{i/t} = \begin{pmatrix} O_{1\times t-1} & 1 & 0 & O_{1\times T(i)-S(i)-t} \end{pmatrix},$$

such that $M_{i/t}$ filters the t^{th} row out of the matrix and $\overline{M}_{i/t}$ filters all rows except the t^{th}. Thus the moments of the univariate conditional truncated distributions for e_{it} are given as

$$\begin{aligned}
\overline{\mu}_{e_{it}} &= (\overline{M}_{i/t}\mu_{e_{i\cdot}}) + \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)\left(M_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)^{-1}(M_{i/t}(e_{i\cdot} - \mu_{e_{i\cdot}}), \\
\overline{\sigma}^2_{e_{it}} &= \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}\overline{M}'_{i/t}\right) - \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)\left(M_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)^{-1}\left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)'.
\end{aligned}$$

The truncation sphere remains unchanged.

(vi) Finally, define

$$\varrho_{i\cdot} = \delta^*_{i\cdot} - X^{\mathrm{ran}}_{i\cdot}\beta_i.$$

The vector of fixed parameters corresponding to fixed variables $\overline{\beta}$ is hence sampled from a multivariate normal distribution $(\mu_{\overline{\beta}}, \Sigma_{\overline{\beta}})$, where

$$\begin{aligned}
\mu_{\overline{\beta}} &= \left(\sum_{i=1}^{N}\left(\overline{X}'_{i\cdot}\Sigma_i^{-1}\overline{X}_{i\cdot}\right) + \Omega^{-1}_{\overline{\beta},0}\right)^{-1}\left(\sum_{i=1}^{N}\left(\overline{X}'_{i\cdot}\Sigma_i^{-1}\varrho_{i\cdot}\right) + \Omega^{-1}_{\overline{\beta},0}\mu_{\overline{\beta},0}\right), \\
\Sigma_{\overline{\beta}} &= \left(\sum_{i=1}^{N}\left(\overline{X}'_{i\cdot}\Sigma_i^{-1}\overline{X}_{i\cdot}\right) + \Omega^{-1}_{\overline{\beta},0}\right)^{-1}
\end{aligned}$$

and $\mu_{\overline{\beta},0}$, $\Omega_{\overline{\beta},0}$ denote the corresponding prior moments.

2.7.2 Treatment Model with Serial Correlation and partial Heterogeneity via Random Coefficients

The treatment model with serial correlation and partially assigned random coefficients is given in Equations (2.14)-(2.21). Gibbs sampling for this model specification builds on the set of full conditional distributions for $\{\theta_i = (\beta_i, \alpha_i)\}_{i=1}^N$, b, W_b, a, W_a, ρ, σ^2, ψ, $\{\{e_{it}\}_{t=S(i)}^{T(i)}\}_{i=1}^N$ and $\overline{\theta} = (\overline{\beta}, \overline{\alpha})$. Define the covariance of the composed error vector $(\epsilon_{i\cdot}, e_{i\cdot})'$ as

$$\Omega_i = \left(\begin{array}{cccccccc} \sigma^2 & 0 & \dots & 0 & \psi & \rho\psi & \cdots & \rho^{T(i)-S(i)+1}\psi \\ 0 & \sigma^2 & \dots & 0 & 0 & \psi & & \vdots \\ \vdots & & \ddots & 0 & \vdots & 0 & \ddots & \rho\psi \\ 0 & \cdots & 0 & \sigma^2 & 0 & \cdots & 0 & \psi \\ \psi & 0 & \cdots & 0 & \frac{1}{1-\rho^2} & \frac{\rho}{1-\rho^2} & \cdots & \frac{\rho^{T(i)-S(i)}}{1-\rho^2} \\ \rho\psi & \psi & 0 & \vdots & \frac{\rho}{1-\rho^2} & \frac{1}{1-\rho^2} & & \vdots \\ \vdots & & \ddots & 0 & \vdots & & \ddots & \\ \rho^{T(i)-S(i)+1}\psi & \cdots & \rho\psi & \psi & \frac{\rho^{T(i)-S(i)}}{1-\rho^2} & \cdots & & \frac{1}{1-\rho^2} \end{array} \right).$$

The full conditional distributions are given as follows.

(i) For each individual i a vector of random coefficients is drawn from the multivariate normal distribution $\mathcal{N}(\mu_{\theta_i}, \Sigma_{\theta_i})$. Define

$$H_i^{\text{ran}} = \begin{pmatrix} Z_i^{\text{ran}} & 0 \\ 0 & X_i^{\text{ran}} \end{pmatrix} \quad \text{and} \quad \xi_{i\cdot} = \begin{pmatrix} gr_{i\cdot} - \overline{Z}'_{i\cdot}\overline{\alpha} \\ \delta^*_{i\cdot} - \overline{X}'_{i\cdot}\overline{\beta} \end{pmatrix}$$

and

$$\Omega_{\theta_i} = \begin{pmatrix} W_a & 0 \\ 0 & W_b \end{pmatrix} \quad \mu_{\theta_i} = \begin{pmatrix} a \\ b \end{pmatrix}.$$

Hence

$$\begin{aligned} \mu_{\theta_i} &= \left(H_{i\cdot}^{\text{ran}\prime}\Omega_i^{-1}H_{i\cdot}^{\text{ran}} + \Omega_{\theta_i}^{-1}\right)^{-1}\left(H_{i\cdot}^{\text{ran}\prime}\Omega_i^{-1}\xi_{i\cdot} + \Omega_{\theta_i}^{-1}\mu_{\theta_i}\right) \\ \Sigma_{\theta_i} &= \left(H_{i\cdot}^{\text{ran}\prime}\Omega_i^{-1}H_{i\cdot}^{\text{ran}} + \Omega_{\theta_i}^{-1}\right)^{-1}. \end{aligned}$$

(ii.a+b) (a) When a conjugate normal prior with moments (μ_{a0}, Ω_{a0}) is assumed, the mean parameter a is sampled conditional on the country specific random coefficients $\{\alpha_i\}_{i=1}^N$ from a multivariate normal distribution $\mathcal{N}(\mu_a, \Sigma_a)$, where

$$\begin{aligned} \mu_a &= \left(NW_a^{-1} + \Omega_{a0}^{-1}\right)^{-1}\left(NW_a^{-1}\left(\frac{1}{N}\sum_{i=1}^N \alpha_i\right) + \Omega_{a0}^{-1}\mu_{a0}\right), \\ \Sigma_a &= \left(NW_a^{-1} + \Omega_{a0}^{-1}\right)^{-1}. \end{aligned}$$

(b) When a conjugate normal prior with moments (μ_{b0}, Ω_{b0}) is assumed, the mean parameter b is sampled conditional on the country specific random coefficients $\{\beta_i\}_{i=1}^N$ from a multivariate normal distribution $\mathcal{N}(\mu_b, \Sigma_b)$, where

$$\begin{aligned}
\mu_b &= \left(NW_b^{-1} + \Omega_{b0}^{-1}\right)^{-1} \left(NW_b^{-1}\left(\frac{1}{N}\sum_{i=1}^N \beta_i\right) + \Omega_{b0}^{-1}\mu_{b0}\right), \\
\Sigma_b &= \left(NW_b^{-1} + \Omega_{b0}^{-1}\right)^{-1}.
\end{aligned}$$

(iii.a+b) (a) The covariance matrix of the random coefficients can either be diagonal or allowing for correlation between the parameters. In case of a diagonal matrix and when conjugate inverse gamma priors $\mathcal{IG}(\alpha_{W_a^{jj}0}, \beta_{W_a^{jj}0})$ are used, the diagonal elements W_a^{jj}, $j = 1, \ldots, \text{ran}_a$ are sampled independently from inverse gamma distributions $\mathcal{IG}(\alpha_{W_a^{jj}}, \beta_{W_a^{jj}})$, where

$$\alpha_{W_a^{jj}} = \frac{N}{2} + \alpha_{W_a^{jj}0}, \quad \beta_{W_a^{jj}} = \frac{1}{2}\sum_{i=1}^N (\alpha_i^{jj} - a^{jj})^2 + \beta_{W_a^{jj}0}.$$

In case of a full specified matrix, W_a is sampled from an inverted Wishart distribution $\mathcal{IW}(q_{W_a}, S_{W_a})$ with an inverted Wishart $\mathcal{IW}(q_{W_a0}, S_{W_a0})$ as a prior distribution. Consequently,

$$\begin{aligned}
q_{W_a} &= q_{W_a0} + N, \\
S_{W_a} &= q_{W_a0}S_{W_a0} + \left(\sum_{i=1}^N (\alpha_i - a)(\alpha_i - a)'\right).
\end{aligned}$$

(b) The covariance matrix of the random coefficients can either be diagonal or allowing for correlation between the parameters. In case of a diagonal matrix and when conjugate inverse gamma priors $\mathcal{IG}(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})$ are used, the diagonal elements W_b^{jj}, $j = 1, \ldots, \text{ran}_b$ are sampled independently from inverse gamma distributions $\mathcal{IG}(\alpha_{W_b^{jj}}, \beta_{W_b^{jj}})$, where

$$\alpha_{W_b^{jj}} = \frac{N}{2} + \alpha_{W_b^{jj}0}, \quad \beta_{W_b^{jj}} = \frac{1}{2}\sum_{i=1}^N (\beta_i^{jj} - b^{jj})^2 + \beta_{W_b^{jj}0}.$$

In case of a full specified matrix, W_b is sampled from an inverted Wishart distribution $\mathcal{IW}(q_{W_b}, S_{W_b})$ with an inverted Wishart $\mathcal{IW}(q_{W_b0}, S_{W_b0})$ as a prior distribution. Consequently,

$$\begin{aligned}
q_{W_b} &= q_{W_b0} + N, \\
S_{W_b} &= q_{W_b0}S_{W_b0} + \left(\sum_{i=1}^N (\beta_i - b)(\beta_i - b)'\right).
\end{aligned}$$

(iv) The serial correlation parameter is obtained according to Step (iv) for the probit specification above. Therefore, the serial correlation parameter ρ is obtained via regressing the standardized residuals of the probit equation on their lagged counterparts. Define

$$\zeta_i^1 = \left(e_{iS(i)} \frac{\sigma}{\sqrt{\sigma^2 - \psi^2}}, \ldots, e_{iT(i)-1} \frac{\sigma}{\sqrt{\sigma^2 - \psi^2}} \right)' \quad \text{and}$$

$$\zeta_i^2 = \left((e_{iS(i)+1} - \frac{\psi^2}{\sigma^2} \epsilon_{iS(i)}) \frac{\sigma}{\sqrt{\sigma^2 - \psi^2}}, \ldots, (e_{iT(i)} - \frac{\psi^2}{\sigma^2} \epsilon_{iT(i)}) \frac{\sigma}{\sqrt{\sigma^2 - \psi^2}} \right)'.$$

Hence, given a uniform prior, ρ is sampled from a truncated normal distribution $\mathcal{N}_{\mathcal{T}_\rho}(\mu_\rho, \sigma_\rho^2)$, where

$$\mu_\rho = (\zeta_i^{1'} \zeta_i^1)^{-1} (\zeta_i^{1'} \zeta_i^2), \quad \sigma_\rho^2 = (\zeta_i^{1'} \zeta_i^1)^{-1}, \quad \mathcal{T}_\rho = (-1, 1).$$

(v) The correlation between the two equations captured via parameter ψ is obtained via regressing the residuals of one equation on their counterparts from the other. Note that

$$\begin{pmatrix} \epsilon_{it} \\ u_{it} \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \psi \\ \psi & 1 \end{pmatrix} \right).$$

Standardizing ϵ_{it} on u_{it} elementwise by σ and regressing $\tilde{\epsilon}_{it} = \frac{\epsilon_{it}}{\sqrt{\sigma^2 - \psi^2}}$ on $\tilde{u}_{it} = \frac{u_{it}}{\sqrt{\sigma^2 - \psi^2}}$ leads to the full conditional distribution of ψ given as a normal distribution $\mathcal{N}_{\mathcal{T}}(\mu_\psi, \sigma_\psi^2)$, when a normal prior is assumed. Hence

$$\mu_\psi = \left(\sum_{i=1}^N \tilde{u}_{i\cdot}' \tilde{u}_{i\cdot} + \frac{1}{\sigma_{\psi 0}^2} \right)^{-1} \left(\sum_{i=1}^N \tilde{u}_{i\cdot}' \tilde{\epsilon}_{i\cdot} + \frac{\mu_{\psi 0}}{\sigma_{\psi 0}^2} \right), \qquad \sigma_\psi^2 = \left(\sum_{i=1}^N \tilde{u}_{i\cdot}' \tilde{u}_{i\cdot} + \frac{1}{\sigma_{\psi 0}^2} \right)^{-1}.$$

Note that standardization by the conditional variance $\sigma^2 - \psi^2$ does not violate the Gibbs principle, as in the next step only the conditional variance is sampled.

(vii) The unconditional variance of the growth equation σ is obtained via sampling the conditional variance and adding the part stemming from the covariance. Starting point is again the conditional distribution $\epsilon_{it}|u_{it}$. The conditional variance $\zeta = \sigma^2 - \psi^2$ is hence sampled from an inverse gamma distribution $\mathcal{IG}(\alpha_\zeta, \beta_\zeta)$, where

$$\alpha_\zeta = \left(\frac{1}{2} \sum_{i=1}^N (T(i) - S(i) + 1) \right) + \alpha_{\zeta 0}, \qquad \beta_\zeta = \left(\frac{1}{2} \sum_{i=1}^N \sum_{t=S(i)}^{T(i)} (\epsilon_{it} - u_{it}\psi)^2 \right) + \beta_{\zeta 0}.$$

(viii) The Bayesian estimation approach allows to linearize the model via inclusion of the latent dependent variable δ_{it}^* computed via

$$\delta_{it}^* = \overline{X}_{i\cdot} \overline{\beta} + X_{i\cdot}^{\text{ran}_b} \beta_i + e_{it}$$

As gr_{it} and δ_{it}^* are jointly normal distributed, the latent error $e_{i\cdot}$ is sampled from a multivariate truncated normal distribution conditional on the errors of the growth equation $\epsilon_{i\cdot}$. Define $\Omega_{\epsilon,e}$ as upper right block of Ω_i capturing the covariance of $\epsilon_{i\cdot}$ and $\eta_{i\cdot}$, Σ_ϵ as upper left block of Ω_i capturing the covariance of $\epsilon_{i\cdot}$ and Σ_i as lower right block of Ω_i. Thus

$$e_{i\cdot} \sim \mathcal{N}_{\mathcal{T}_{e_{i\cdot}}}(\mu_{e_{i\cdot}}, \Sigma_{e_{i\cdot}}),$$

where

$$
\begin{aligned}
\mu_{e_{i\cdot}} &= \Omega'_{\epsilon,e^*}\Sigma_\epsilon^{-1}(\epsilon_{i\cdot}) \\
\Sigma_{e_{i\cdot}} &= \Sigma_i - \Omega'_{\epsilon,e}\Sigma_\epsilon^{-1}\Omega_{\epsilon,e}, \\
\mathcal{T}_{e_{i\cdot}} &= (\sqcup_{D(i)},\ldots,\sqcup_{T(i)})', \\
\sqcup_t &= \begin{cases} (-(\overline{X}'_{it}\overline{\beta} + X_{it}^{\text{ran}_b\prime}\beta_i),\infty), & \text{if } \delta_{it}=1 \\ (-\infty,-(\overline{X}'_{it}\overline{\beta} + X_{it}^{\text{ran}_b\prime}\beta_i)), & \text{if } \delta_{it}=0 \end{cases}, \quad t = S(i),\ldots,T(i).
\end{aligned}
$$

As draws from a multivariate truncated normal distribution cannot be obtained from a closed form density, the algorithm of Geweke (1991) is employed. Each element of $e_{i\cdot}$ is drawn conditional on all other elements from a univariate truncated normal distribution. Denote $I_{k\times k}$ as identity matrix and $O_{k\times k}$ as a matrix containing only zeros. Hence, define for $t = 1,\ldots,T(i)-S(i)+1$

$$
M_{i/t} = \begin{pmatrix} I_{t-1\times t-1} & O_{t-1\times 1} & O_{t-1\times 1} & O_{t-1\times T(i)-S(i)-t} \\ O_{1\times t-1} & 0 & 1 & O_{1\times T(i)-S(i)-t} \\ O_{T(i)-S(i)-t\times t-1} & O_{T(i)-S(i)-t\times 1} & O_{T(i)-S(i)-t\times 1} & I_{T(i)-S(i)-t\times T(i)-S(i)-t} \end{pmatrix}
$$

and

$$
\overline{M}_{i/t} = \begin{pmatrix} O_{1\times t-1} & 1 & 0 & O_{1\times T(i)-S(i)-t} \end{pmatrix},
$$

such that $M_{i/t}$ filters the t^{th} row out of matrix and $\overline{M}_{i/t}$ filters all rows except the t^{th}. Therefore the moments of the univariate conditional truncated distributions for e_{it} are given as

$$
\begin{aligned}
\overline{\mu}_{e_{it}} &= (\overline{M}_{i/t}\mu_{e_{i\cdot}}) + \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)\left(M_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)^{-1}(M_{i/t}(e_{i\cdot}-\mu_{e_{i\cdot}}), \\
\overline{\sigma}^2_{e_{it}} &= \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}\overline{M}'_{i/t}\right) - \left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)\left(M_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)^{-1}\left(\overline{M}_{i/t}\Sigma_{e_{i\cdot}}M'_{i/t}\right)'.
\end{aligned}
$$

The truncation sphere remains unchanged.

(ix) Finally, the vector of fixed parameters is drawn from a multivariate normal distribution $\mathcal{N}(\mu_{\overline{\theta}},\Sigma_{\overline{\theta}})$. Define

$$
\overline{H}_{i\cdot} = \begin{pmatrix} \overline{Z}_{i\cdot} & 0 \\ 0 & \overline{X}_{i\cdot} \end{pmatrix} \quad \text{and} \quad \xi_{i\cdot} = \begin{pmatrix} gr_{i\cdot} - Z_{i\cdot}^{\text{ran}_a}\alpha_i \\ \delta^*_{i\cdot} - X_{i\cdot}^{\text{ran}_b}\beta_i \end{pmatrix}.
$$

Hence with $\mu_{\overline{\theta},0}$ and $\Omega_{\overline{\theta},0}$ denoting the prior moments

$$
\begin{aligned}
\mu_{\overline{\theta}} &= \left(\left(\sum_{i=1}^{N}\overline{H}_{i\cdot}\Omega_i^{-1}\overline{H}_{i\cdot}\right) + \Omega_{\overline{\theta},0}^{-1}\right)^{-1}\left(\left(\sum_{i=1}^{N}\overline{H}'_{i\cdot}\Omega_i^{-1}\xi_{i\cdot}\right) + \Omega_{\overline{\theta},0}^{-1}\mu_{\overline{\theta},0}\right), \\
\Sigma_{\overline{\theta}} &= \left(\left(\sum_{i=1}^{N}\overline{H}'_{i\cdot}\Omega_i^{-1}\overline{H}_{i\cdot}\right) + \Omega_{\overline{\theta},0}^{-1}\right)^{-1}
\end{aligned}
$$

and $\mu_{\overline{\theta},0}$, $\Omega_{\overline{\theta},0}$ denote the corresponding prior moments.

2.7.3 Distributional Forms and Specification of Prior Moments

In the following the functional forms of the densities employed within the calculation of the posterior can be summarized as follows.

1. *Multivariate Normal*:
   Let $x \in R^p$, $\mu \in R^p$ and Σ be a positive definite matrix of dimension $p \times p$. Then
   $$f_{\mathcal{N}}(x; \mu, \Sigma) = (2\pi)^{-\frac{p}{2}} |\Sigma|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(x-\mu)'\Sigma^{-1}(x-\mu)\right).$$
2. *Inverse Gamma*:
   Let x be a scalar and $\alpha, \beta > 0$. Then
   $$f_{\mathcal{IG}}(x; \alpha, \beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{-(\alpha+1)} \exp\left(-\frac{\beta}{x}\right).$$
3. *Univariate Truncated Normal*:
   Let $x \in [l, u]$ and Φ denote the cumulative density of a standard normal distribution. Then
   $$f_{\mathcal{N_T}}(x; \mu, \sigma) = \frac{(2\pi)^{-\frac{1}{2}}\sigma^{-1} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)}{\Phi(\frac{u-\mu}{\sigma}) - \Phi(\frac{l-\mu}{\sigma})}.$$

Robustness of the results are checked with against alternative specifications of variance priors. The sensitivity of results with respect to priors of the mean parameters are not subject of discussion, since for all mean parameters the corresponding functional forms and prior moments imply a non informative setting with a large variance of 1000.

The three considered variance prior scenarios correspond to different a prior variance levels for variance parameters. The effect of the different prior scenarios can be illustrated in terms of the moments for the related precisions. The scenario with hyperparameters equal to five imply a mean of one and variance of 0.2, while scenario $\bullet$ yields a prior mean and variance equal to one. Scenario $\bullet\bullet$ with hyperparameters equal to ten implies also a mean of 1, but a variance of 0.1. Hence the scenario $\bullet$ is least informative as it implies the largest a priori variance. The following Table (2.19) summarizes the hyperparameters of the prior distributions. $I_{k \times k}$ denotes an identity matrix and subscripts $_{\text{ran}}$, $_{\text{fix}}$, $_{\text{ran}_a}$ and $_{\text{ran}_b}$ denote the corresponding number of random coefficients.

Tab. 2.19: Hyperparameters of prior distributions

	Probit Model		
(μ_{b0}, Ω_{b0})	$\mathcal{N}$	0	$I_{\mathrm{ran}\times\mathrm{ran}} \cdot 1000$
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\mathrm{ran}}$	$\mathcal{IG}$	5	5
$(\mu_{\overline{\beta}0}, \Omega_{\overline{\beta}0})$	$\mathcal{N}$	0	$I_{\mathrm{fix}\times\mathrm{fix}} \cdot 1000$
	Treatment Model		
(μ_{a0}, Ω_{a0})	$\mathcal{N}$	0	$I_{\mathrm{ran}_a\times\mathrm{ran}_a} \cdot 1000$
(μ_{b0}, Ω_{b0})	$\mathcal{N}$	0	$I_{\mathrm{ran}_b\times\mathrm{ran}_b} \cdot 1000$
$\{(\alpha_{W_a^{jj}0}, \beta_{W_a^{jj}0})\}_{j=1}^{\mathrm{ran}_a}$	$\mathcal{IG}$	5	5
$\{(\alpha_{W_a^{jj}0}, \beta_{W_a^{jj}0})\}_{j=1}^{\mathrm{ran}_a}$ (•)	$\mathcal{IG}$	1	1
$\{(\alpha_{W_a^{jj}0}, \beta_{W_a^{jj}0})\}_{j=1}^{\mathrm{ran}_a}$ (••)	$\mathcal{IG}$	10	10
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\mathrm{ran}_b}$	$\mathcal{IG}$	5	5
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\mathrm{ran}_b}$ (•)	$\mathcal{IG}$	1	1
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\mathrm{ran}_b}$ (••)	$\mathcal{IG}$	10	10
(q_{W_b0}, S_{W_b0})	–	–	–
$(\mu_{\psi0}, \sigma^2_{\psi0})$	$\mathcal{N}$	0	1000
$(\alpha_{\zeta0}, \beta_{\zeta0})$	$\mathcal{IG}$	1	1
$(\mu_{\overline{\beta}0}, \Omega_{\overline{\beta}0})$	$\mathcal{N}$	0	$I_{\mathrm{fix}\times\mathrm{fix}} \cdot 1000$

3. COSTS OF CURRENT ACCOUNT REVERSALS AND CURRENCY CRISES

3.1 Introduction

Macroeconomic crises often trigger adjustment processes characterized by painful deteriorations of economic growth. Well known examples are the lessons from the Mexican crisis in 1994 and the crises in Argentina in the 1990ies. The occurrence of macroeconomic crises often involve currency crises connected to large depreciations of exchange rates preceded in case of pegged exchange rates by a depletion of international reserves. Such turbulences causing abrupt changes in the terms of trade and other prices can induce demand driven boom-bust cycles linked to the observation of induced current account reversals. Links between these two crises phenomena, also incorporated in several theoretical models concerned with inflation stabilization, see Calvo and Vegh (1999) for an overview, have been analyzed by Milesi-Ferretti and Razin (2000). The empirical literature nevertheless often captures crises episodes either via concentrating on large exchange rate and reserve level fluctuations, see e.g. Kaminsky and Reinhart (1999), or via focusing on reverting current account balances, see e.g. Edwards (2004). The previous Chapter 3 added to this strand of analysis of crises the incorporation of latent heterogeneity and serial correlation. However, incorporation of the relationship between currency crises and current account reversals as investigated below in Section 2 of this chapter by means of a χ^2-test of independence may be essential to allow a correct assessment of the influence both crises phenomena have on economic growth.

Several articles in the empirical literature ignore the relationship between both crises phenomena and provide the following conclusions concerning the influence of these specific crises indicators on economic growth. Using the econometric methodology of Arellano and Bond (1991), Edwards (2001) highlights the negative impact of current account reversals on economic growth via controlling for indirect effects stemming from investment and the role large current account deficits play in financial crises episodes. Using a panel of six East Asian countries Moreno (1999) analyzes the large output contractions observed in the aftermath of crises episodes. Gupta et al. (2003) provide mixed evidence concerning the question whether currency crises have contractionary or expansionary effects on growth. Their analysis also establishes some stylized facts for currency crises. Currency crises on average cause an output contraction and revert growth to previous levels by the second year after the crises, but a considerable degree of heterogeneity is present. Currency crises occurring in the 1990ies have not caused larger output contraction compared to crises episodes in the 1970ies and 1980ies. Furthermore, larger emerging countries experience more contractionary crises than smaller ones. The idea of heterogeneity in the influence of crises depending on country specifics is also put forward by Edwards (2004) who finds that current account reversals are less severe for more open economies, see also the analysis of the previous chapter.

As stated above, Milesi-Ferretti and Razin (2000) analyze the empirical regularities of both crises phenomena. They observe that currency crises are often followed by reversal episodes. This observation poses two questions. First, are external currency crises inevitably followed by sharp reductions in current account deficits, and second, what is the effect of currency crises and reversals in current account balances on economic performance revealed in simultaneous analysis of both crises phenomena. Milesi-Ferretti and Razin (2000) answer these two questions using probit regressions for each type of crises measure and assess the impact of both events on economic growth by a "before-after" analysis regressing growth before and after the crises event on the binary indicators. Their main finding is that although currency crises are often followed by reversal episodes, both events exhibit distinct properties and show different influence on economic growth with reversal showing no systematic impact on growth, while currency crises cause a growth reduction. Also Komarek and Melecky (2005) provide a joint analysis of both crises. In their study they find in contrast to Milesi-Ferretti and Razin (2000) a systematic slowdown of economic growth given the occurrence of a current account reversal but no impact of currency crises on growth. Komarek and Melecky (2005) also document that highest costs arise for a country, when both crises occur simultaneously.

Given this empirical evidence on the influence of crises from models ignoring links incorporated by several theoretical models between the two crises indicators and economic growth, this chapter fills some gaps in explaining crises and assessment of their influence on economic growth. The above cited literature ignores either the links between currency crises and current account reversals completely, or does not fully acknowledge possible intertemporal dependence between both crises.

Hence, this chapter provides a joint analysis of currency crises and current account reversals and extends hence the analysis presented in Chapter 2 via incorporation of intertemporal linkages between both crises phenomena. Furthermore, the estimated effect on economic growth is controlled for possible sample selection. Shocks hitting economic growth may thus also affect the occurrence probability of crises. Ignoring this correlation would lead to biased estimates of the effect of crises on economic growth. Therefore, a joint model is needed to assess the effects correctly. Next to possible sample selection, intertemporal links are incorporated via explicit consideration of sources of serial dependence. The proposed model framework addresses three sources of serial dependence for currency crises and current account reversals. First, serial dependence is considered via lagged crises, since the experience of past crises may affect the future occurrence probability of crises. Secondly, transitory shocks affecting the growth process and the occurrence of crises are incorporated via serial correlated errors. Thirdly, latent country specific factors possibly stemming from unobserved variables may exhibit a persistent effect on crises and economic growth. This latent heterogeneity provides a source for serial dependence and possibly alters the interaction of crises and economic growth. This latent heterogeneity is captured via random coefficients within the growth equation and provides country specific growth dynamics. Also within the equations explaining the occurrence of crises random coefficients are considered, which capture different institutional settings and economic conditions within the countries. The notion that controlling for serial dependence is essential in binary models is discussed at full length by Hyslop (1999). Falcetti and Tudela (2006) also discuss these issues and document the presence of heterogeneity and serial dependence in the context of explaining currency crises.

A further advantage of a joint modeling of economic growth, current account reversals, and currency crises with several sources of serial dependence is its capability to trace more realistically the effect of crises on economic growth over time. A shock causing the occurrence of a currency crises may simultaneously effect the growth process and the occurrence of a current account reversal. Also the next periods probability of a reversal may be altered thus rising the probability of a current account reversal in the next period and consequently causing further damage to economic growth. Therefore, the incorporation of several sources for serial dependence as well as heterogeneity allows a better approximation of cumulative output losses generated by the occurrence of crises.

Estimation is performed via a Simulated Maximum Likelihood approach. As the likelihood function of the trivariate treatment type model given the features considered above involves high dimensional integrals, estimation is performed using simulation techniques. To obtain accurate estimates an Efficient Importance Sampler following Liesenfeld and Richard (2007) is employed. The developed sampler incorporates the considered model features of serially correlated errors and country specific latent heterogeneity. It therefore enlarges the range of available Efficient Importance Sampler for multiperiod discrete choice models documented in the literature. The Efficient Importance Sampler is assessed within a simulation study and provides a huge (10 to 100 fold) reduction of numerical simulation errors compared to the baseline GHK-sampler documented in Geweke and Keane (2001). It hence allows to evaluate 50 dimensional integrals with the required numerical precision.

The findings of this chapter can be summarized as follows. Both types of crises are associated with a growth slowdown, which is linked for reversals to country size and trade openness. While neglecting endogeneity causes an upward bias for the estimated effect of current account reversals on economic growth, no significant sample selection bias is found for a currency crisis. Also, currency crises are found to be important predictors of current account reversals. Consideration of this intertemporal relationship seems essential to provide a valid assessment of the costs involved in the occurrence of current account reversals. Furthermore, the results document the presence of unobserved heterogeneity and state dependence, which has to be taken into consideration in order to assess the determinants and costs of crises correctly.

The chapter is organized as follows. Within Section 3.2, the data set employed in Chapter 3 for assessment of the joint influence of current account reversals and currency crises on economic growth is described. Section 3.3 presents the empirical models and the applied estimation methodology. The empirical results are given in Section 3.4. Section 3.5 concludes.

3.2 Crises Indicators and Theoretical Background of Explaining Variables

To investigate the relationship between the two crises phenomena and the circumstances, which allow a country to hinder a spreading of crises on the real economy, the following data set is used. Data is taken from the Global Development Finance database of the World Bank, the World Development Indicators (also World Bank), the International Financial Statistics and the Balance of Payments database, both International Monetary Fund. Not all variables of interest are available for all periods from 1975 to 1997, which is the time period used to construct the currency crises indicator, thus resulting in an unbalanced panel, where 67 countries are included for analysis.

The definition of a current account reversal follows Milesi-Ferretti and Razin (1998). A reversal episode in period t is given when the current account balance in t is indeed a deficit and the average current account deficit in the periods t to $t+2$ compared to the average current balance over periods $t-3$ to $t-1$ is reduced by at least 3%. A further restriction is that for a current account reversal the deficit level after the reversal does not exceed 10%. In order to avoid that the same reductions show up twice in the averages, the dynamics in the aftermath of a reversal is restricted. Within the two periods after a reversal no further one is allowed. Moreover, the maximum deficit after a reversal is not allowed to exceed the minimum deficit before the reversal in order to classify the period as a reversal. As should be noted, Chapter 3 focuses on reversal identification scheme III employed in Chapter 2. This is based on the findings of Chapter 2 indicating the robustness of empirical results against the underlying reversal definition. Furthermore, concentration on a single reversal identification scheme reduces substantially the number of model specifications to be estimated.

The episodes of currency crises are taken from Glick and Hutchinson (2005). They define a currency crisis upon a monthly index of currency pressure, defined as a weighted average of real exchange rate changes and monthly reserve losses taken from the International Financial Statistics database.[1] A currency crisis occurs, when changes in the pressure index exceed 5% and are larger than the country specific mean plus two times the country specific standard deviation. Dependence between the two crises indicators can be assessed via a χ^2-test of independence, see Table (3.3). While no significant contemporaneous dependence is found, lagged currency crises and present current account reversals show strong dependency, see also Milesi-Ferretti and Razin (2000). This finding should be incorporated, when modeling the occurrence of crises and the effect of both crises on economic growth and provides a motivation for performing a simultaneous analysis of both crises phenomena based on an extended treatment framework.

Tables (3.1) and (3.2) list the occurrence of current account reversals and currency crises for the considered panel of countries. Note, since the crises indicator is taken from the literature for comparison, this data set is different with respect to the considered sample of countries and the considered time range, which is 1975-1997, compared to the previous chapter.

As explaining variables for growth and both types of crises, the following set is included

[1] The weights are inversely chosen to the variance of each component, see Kaminsky and Reinhart (1999) for details.

as suggested by different theories. The lagged growth rate, the ratio of international reserves to broad money, investment proxied by gross fixed capital formation relative to GDP, current account deficits, trade openness, life expectancy at birth, GDP per capita in 1984 in 1000 US$, US real interest rates, and the OECD growth rates. Summary statistics are given in Table (3.4). The global variables, US real interest rates and OECD growth rates, capture the state of the world business cylce and the state of international financial markets affecting a countries access to international capital. The important role of the international borrowing constraint has been emphasized by Atkeson and Rios-Rull (1996). A theoretical link between investment, growth and current account balance is formalized in the balance-of-payments stages hypothesis in the work of Fischer and Franklin (1974). Life expectancy functions as a proxy of productivity thus enhancing growth, while higher GDP per capita reflects a higher level of development, where higher developed countries are expected to grow less faster. The ratio of international reserves to broad money functions as an indicator of financial institutional development. On the one hand, a developed financial sector provides intermediary services, which should cause higher growth, on the other hand it should lower the risk of the considered crises.

The idea that both types of crises are closely interrelated comes up from several theoretical models established in the literature. These models, see e.g. Calvo and Vegh (1999), deal with the matter of inflation stabilization. Macroeconomic stabilization programs aiming at disinflation are assumed to cause an output contraction either at the start of the program, when a money based stabilization is implemented, or, when an exchange rate based stabilization is chosen, a later recession is likely to occur at the end of the program, see Hoffmaister and Vegh (1996) for a discussion of the “recession-now-versus-recession-later” hypothesis. The choice of the nominal anchor is, besides a choice for the timing of recession, a choice between cumulative losses involved in these crises. Various models, see Calvo and Vegh (1999) for an overview, show that stabilization programs may cause in the presence of inflation inertia or lack of credibility a currency crisis, as a formerly fixed exchange rate breaks down, thus leading furthermore to a reversing current account balance. As illustrated by the seminal model of Krugman (1979) with a fixed exchange rate mechanism, a lower interest rate on international reserves would result in faster depletion of reserves, thus enhancing the losses in reserves causing possibly a currency crises. A run on international reserves may also cause a shortening in domestic credit, as the domestic aggregate money supply decreases, see for a short discussion Flood, Garber and Kramer (1996). As argued by Milesi-Ferretti and Razin (2000) a shortening of external financing via rising world interest rates may cause a current account reversal in order to remain solvent. Decreases in domestic credit may cause a shortening in investment, especially in less developed countries (LDC), as these do not necessarily have full access to international financing. Thus a shock altering domestic credit growth and/or access to international capital markets caused by capital market liberalization as analyzed by Glick and Hutchinson (2005) may lead to alterations in a country’s exposure to both types of crises. Other shocks, e.g. a temporarily income shock caused by an uprise of international prices for commodities can also influence the exposure to crises. Such an income shock, which can be temporarily or permanent, may cause a reduction in current account deficits, see Kraay and Ventura (1997) for a more complete discussion. Alterations in export prices also effect the terms of trade, which can lead according to Tornell and Lane (1998) to ambiguous effects on current account balance. This set of different theories provides the background for the empirical models used to assess the effect of crises on growth in Chapter 3.

3.3 Model Description

This section presents the applied panel frameworks used for the analysis. Also the employed estimation methodology is introduced. Starting point is a panel model, where the effect of both crises on economic growth is considered. Two forms of heterogeneity are taken into account. The costs of crises are linked to observable specifics of a country, and the model accounts for latent country specific heterogeneity stemming from unobservable factors. Several models incorporating these two forms of heterogeneity at different degrees are considered. Afterwards, a trivariate treatment type model is analyzed in order to capture the possible endogeneity of the crises events.

3.3.1 Linear Panel Model

As a starting point a panel model for economic growth gr_{it} in country i at time t ignoring possible endogeneity of both crises is considered. It takes the form

$$gr_{it} = X_{it}\beta_i + \gamma_{1i}(\,{}_1y_{it}) + \gamma_{2i}(\,{}_2y_{it}) + e_{it}, \quad i = 1, \ldots, n; \quad t = S(i), \ldots, T(i), \tag{3.1}$$

where $S(i)$ denotes the first period available for country i and $T(i)$ the last, X_{it} are (weak) exogenous regressors discussed in the literature on growth and ${}_1y_{it}$ and ${}_2y_{it}$ indicate the occurrence of a currency and reversal crisis respectively. $\gamma_{1i}(\,{}_1y_{it})$ and $\gamma_{2i}(\,{}_2y_{it})$ are functions of the crises events taking the form[2]

$$\gamma_{ji}(\,{}_jy_{it}) = (\delta_j + Z_{ji}\zeta_j)\,{}_jy_{it}, \quad j = \{1, 2\}, \tag{3.2}$$

where the parameters δ_j, $j = \{1, 2\}$ measure the impact of economic growth associated with the occurrence of both types of crises and the parameters ζ_j, $j = \{1, 2\}$ capture the influence of country specific variables Z_{ji} on costs. This setup allows to test several hypothesis concerning the country specific variables Z_{ji}, namely whether currency crises exhibit systematic influence on growth, and whether larger and more open economies suffer more from crises than smaller ones.[3] This type of regression model has been used by Gupta et al. (2003) and Komarek and Melecky (2005) to analyze the output responses to currency crises.

To control for country specific heterogeneity within the growth dynamics and the control variables, a random coefficient approach as discussed and suggested by Zellner (1968) and analyzed in more detail by Swamy (1970, 1971), Swamy and Arora (1972), and Swamy et al. (1988a,

[2] Also a specification incorporating lagged crises indicators has been estimated, but no significant influence has been revealed.

[3] Note that an interaction term between both types of crises measuring an additional effect is not significant in any specification.

1988b, 1989) is estimated.[4] The motivation for such a random coefficient has been concisely formulated by Swamy (1970)[5]

> *... we note that many, if not all, micro units are heterogeneous with regard to the regression coefficient vector in a model. If we proceed blithely with cross section analysis ignoring such heterogeneity, we may be led to erroneous inferences. Application of the random coefficient approach to situations that satisfy the specifying assumptions introduced above leads to correct results.*

This random coefficient specification assumes a multivariate normal distribution for the parameters, which are assumed to bear unobserved country specific heterogeneity. Hence, the random coefficients are specified as

$$\beta_i \overset{\text{iid}}{\sim} \mathcal{N}(b, \Omega), \tag{3.3}$$

thus allowing for correlation between the random coefficients via the covariance matrix Ω.[6] Naturally also a block diagonal structure is possible for Ω when no correlation among the regression coefficients shall be considered. Also the crises indicators cannot be linked to a random coefficient as not all countries experience both crises and thus provide no variability allowing the identification of a random coefficient. The modeling of unobserved heterogeneity via random coefficients provides a parsimonious, yet flexible structure. Specification of fixed effects would in contrast increase the number of parameters rapidly and would cause the occurrence of an incidential parameter problem for the relatively short considered time dimension.

Errors are assumed to follow a moving average process of order one in order to capture via serial correlation unobserved persistence, hence

$$e_{it} = \varphi v_{it-1} + v_{it}, \quad v_{it} \overset{\text{iid}}{\sim} \mathcal{N}(0, \sigma^2). \tag{3.4}$$

Given the assumption of independence of all errors v_{it} and random coefficients β_i, the implied overall covariance structure for a countries growth process $gr_{i\cdot}$ is heteroscedastic given by

$$\Sigma_i + X_i^{\text{ran}\prime} \Omega X_i^{\text{ran}},$$

where Σ_i denotes the covariance matrix of serially correlated errors $e_{i\cdot}$ defined as an moving average process of order one and length $T(i) - S(i) + 1$.

A maximum likelihood estimation is performed. Denoting the vector of all model parameters as θ, the corresponding log likelihood estimator is given as

$$\hat{\theta}_{ML} = \arg\max_{\theta} \ell(gr; \theta) = \sum_{i=1}^{n} \ln \left(\int\limits_{[\times(-\infty,\infty)^k]} \frac{(2\pi)^{-\frac{t_i}{2}}}{\det(\Sigma_i)^{.5}} \exp\left(-\frac{1}{2} e_i' \Sigma_i^{-1} e_i\right) f(\beta_i) d\beta_i \right), \tag{3.5}$$

[4] See Swamy and Tavlas (1995, 2001) for surveys on random coefficient models.

[5] Zellner (1968) provides a motivation for the use of the random coefficient approach on the basis of the aggregation problem arising for macroeconomic panel data.

[6] Note that if X_{it} incorporates country specific time invariant regressors besides the constant no random coefficient can be assigned to these for identification purposes.

where t_i denotes the number of observed periods for individual i, k the number of assigned random parameters, $e_i = gr_i - X_i\beta_i - \gamma_{1i}(\cdot) - \gamma_{2i}(\cdot)$ and Σ_i given as the covariance matrix of an MA(1) process of dimension t_i. The integral within the log likelihood can be computed analytically, see Subsection 3.6.1 for details.

The analysis of treatment measured via discrete variables in the above considered framework possibly ignores the endogeneity of both types of crises. Several frameworks suitable to cope with endogeneity and the induced bias in the parameter estimation have been suggested by Maddala (1983). Furthermore, the macroeconomic character of the data asks for a cautious specification of serial correlation within the probit equations explaining the occurrence of both crises. Thus high dimensional integration methods as documented in Geweke and Keane (2001) have to be used. The next section therefore presents a model framework dealing with the matter of endogeneity and gives the used estimation methodology.

3.3.2 Trivariate Panel Treatment Model

To capture the influence both types of crises exhibit on economic growth of a country, a trivariate treatment type model is used allowing for possibly endogeneity of both crises in order to prevent biased estimation. The seminal papers of Heckman (1978) and Heckman (1990) have suggested several model types coping with the endogeneity of one dummy variable. The approach given below extends the setting under consideration of random coefficients to two possible endogenous indicator variables. The growth equation given in Equation (3.1) is linked to two equations explaining the occurrence of both crises, which constitute a bivariate probit model given as

$$ {}_1y_{it} = \begin{cases} 1, & \text{if } {}_1y^*_{it} \geq 0 \\ 0, & \text{if } {}_1y^*_{it} < 0 \end{cases}, \qquad {}_2y_{it} = \begin{cases} 1, & \text{if } {}_2y^*_{it} \geq 0 \\ 0, & \text{if } {}_2y^*_{it} < 0 \end{cases}, \tag{3.6} $$

$$ \begin{aligned} {}_1y^*_{it} &= X^{(1)}_{it}\beta_{1i} + \delta_{11}\ {}_1y_{it-1} + \delta_{12}\ {}_2y_{it-1} + {}_1\epsilon_{it}, & (3.7) \\ {}_2y^*_{it} &= X^{(2)}_{it}\beta_{2i} + \delta_{21}\ {}_1y_{it-1} + \delta_{22}\ {}_2y_{it-1} + {}_2\epsilon_{it}. & (3.8) \end{aligned} $$

Equations (3.7) and (3.8) link the latent variables for currency crises and current account reversals to explanatory factors discussed in the literature. Via inclusion of the lagged binary variables, the model is able to deal with state dependence. Furthermore, as suggested by Falcetti and Tudela (2006), serial correlation is modeled within the error terms, thus capturing correlation of shocks over time. Allowing for serially correlated errors hinders an improper treatment of the conditional relationship between future and past crises called spurious state dependence, see Hyslop (1999). Hence the errors are given as a bivariate autoregressive process of order one, modeled as

$$ \begin{pmatrix} {}_1\epsilon_{it} \\ {}_2\epsilon_{it} \end{pmatrix} = \begin{pmatrix} \varphi_1 & 0 \\ 0 & \varphi_2 \end{pmatrix} \begin{pmatrix} {}_1\epsilon_{it-1} \\ {}_2\epsilon_{it-1} \end{pmatrix} + \begin{pmatrix} {}_1u_{it} \\ {}_2u_{it} \end{pmatrix}. \tag{3.9} $$

With respect to the error structure of the three equation shocks, a trivariate normal distribution is assumed given as

$$\begin{pmatrix} e_{it} \\ {}_1u_{it} \\ {}_2u_{it} \end{pmatrix} \sim \mathcal{N}(0,\Lambda), \quad \Lambda = \begin{pmatrix} \sigma^2 & \psi_1 & \psi_2 \\ \psi_1 & 1 & \rho \\ \psi_2 & \rho & 1 \end{pmatrix} \tag{3.10}$$

where the ones on the main diagonal are set for identification of the parameters within the underlying probit equations. This quite general error structure allows to incorporate forms of serial correlation of shocks between the different equations, allowing for rich intertemporal dependencies. Furthermore, again heterogeneity possibly stemming from differences with regard to the institutional background of countries are taken into consideration via random coefficients assigned to several variables, hence

$$\beta_{1i} \overset{\text{iid}}{\sim} \mathcal{N}(b_1, W_1) \quad \text{and} \quad \beta_{2i} \overset{\text{iid}}{\sim} \mathcal{N}(b_2, W_2). \tag{3.11}$$

Given this model setup one can illustrate the effects arising from the possible endogeneity of crises indicators ${}_jy_{it}, j = \{1,2\}$. Following Angrist et al. (1996), the endogenous regressors ${}_jy_{it}, j = \{1,2\}$ in econometric terminology, are potentially correlated with e_{it} because the disturbances ${}_1\epsilon_{it}$, ${}_2\epsilon_{it}$ and e_{it} are potentially correlated. Using the terminology and phrase of Rubin (1978), this implies that "*. . . the receipt of treatment is not ignorable and, in econometric terminology, not exogenous.*" The selection bias occurring when endogeneity of the crises dummies is ignored can be analyzed as follows. For simplicity assume the random coefficients as given and the absence of any serial correlation structure within the errors. The conditional expectation given the explaining variables and the occurrence of both crises can be expressed as

$$\begin{aligned} E[gr_{it} \mid {}_1y_{it}=1,\ {}_2y_{it}=1, X_{it}] \quad = \quad & X_{it}\beta_i + \gamma_1({}_1y_{it}) + \gamma_2({}_2y_{it}) + \\ & \begin{pmatrix} \psi_1 & \psi_2 \end{pmatrix} \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}^{-1} E\left[\begin{pmatrix} {}_1u_{it} \\ {}_2u_{it} \end{pmatrix} \mid {}_1y^*_{it} > 0,\ {}_2y^*_{it} > 0 \right], \end{aligned} \tag{3.12}$$

where the conditional expectation of the errors of the probit equation conditional on the event of crises has the form

$$E\left[\begin{pmatrix} {}_1u_{it} \\ {}_2u_{it} \end{pmatrix} \mid {}_1y^*_{it} > 0,\ {}_2y^*_{it} > 0 \right] = \begin{pmatrix} \frac{\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\rho\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr(\ {}_1u_{it}>h,\ {}_2u_{it}>k)} \\ \frac{\rho\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr(\ {}_1u_{it}>h,\ {}_2u_{it}>k)} \end{pmatrix}, \tag{3.13}$$

where

$$h = -(X^{(1)}_{it}\beta_{1i} + \delta_{11}\ {}_1y_{it-1} + \delta_{12}\ {}_2y_{it-1}), \qquad k = -(X^{(2)}_{it}\beta_{2i} + \delta_{21}\ {}_1y_{it-1} + \delta_{22}\ {}_2y_{it-1}) \tag{3.14}$$

and $\Pr(\ {}_1u_{it} > h,\ {}_2u_{it} > k))$ is the joint probability derived from the bivariate normal distribution.[7] The expectation in Equation (3.13) is a bivariate extension of the well known Mills's

[7] For a derivation of these moments of the truncated bivariate normal distribution, see Rosenbaum (1961) and Regier and Hamdan (1971).

ratio. Inclusion of Mill's ratio as a further regressor within a two step estimation procedure would also be possible but less efficient than a simultaneous estimation of all parameters. Thus ignoring sample selection mechanism present for covariance and correlation parameters different from zero induces a bias in estimation of parameters capturing the effect of currency crises and current account reversals. The size and sign of bias depends on the covariance structure Λ of the trivariate normal distribution. For example, if $h = k = \rho = 0$, then an upwards bias in parameter estimates is induced for positive correlation between errors of the probit and growth equations.

The model shall be investigated via a Simulated Maximum Likelihood estimation.[8] The properties of the simulation based estimator have been analyzed in detail by Gourieroux and Monfort (1996)[9]. The likelihood contribution of country i can be stated as

$$\begin{aligned} L_i &= \int_{\times(-\infty,\infty)^k} f_{gr_{i\cdot}|\beta_i}(gr_{i\cdot}|\beta_i) \int_{\times(-\infty,\infty)^{k_1+k_2}} \iiint_{R_{1,iS(i)}\cdots R_{1,iT(i)} R_{2,iS(i)} R_{2,iT(i)}} f_{\epsilon_{i\cdot}|gr_{i\cdot}}(\epsilon_{i\cdot}|gr_{i\cdot}) d\epsilon_{i\cdot} \\ & \qquad f(\beta_{1i}, \beta_{2i}) d\beta_{1i} d\beta_{2i} f(\beta_i) d\beta_i, \end{aligned} \tag{3.15}$$

where $\epsilon_{i\cdot} = (\ {}_1\epsilon_{iD(i)},\ {}_1\epsilon_{iT(i)},\ {}_2\epsilon_{iS(i)}, \ldots,\ {}_2\epsilon_{iT(i)})$ and $f_{\epsilon_{i\cdot}|gr_{i\cdot}}(\cdot)$ denotes the conditional distribution of the latent errors given growth $gr_{i\cdot}$, $f_{gr_{i\cdot}|\beta_i}(\cdot)$ the distribution of growth rate for country i conditional on β_i and the range of integration is given as

$$R_{1,it} = \begin{cases} \left(-\infty, -X_{it}^{(1)}\beta_{1i} - \delta_{11}\ {}_1y_{it-1} - \delta_{12}\ {}_2y_{it-1}\right), & \text{if } {}_1y_{it} = 0, \\ \left(-X_{it}^{(1)}\beta_{1i} - \delta_{11}\ {}_1y_{it-1} - \delta_{12}\ {}_2y_{it-1}, \infty\right), & \text{if } {}_1y_{it} = 1; \end{cases} \quad \text{for } {}_1\epsilon_{iS(i)}, \ldots,\ {}_1\epsilon_{iT(i)},$$

$$R_{2,it} = \begin{cases} \left(-\infty, -X_{it}^{(2)}\beta_{2i} - \delta_{21}\ {}_1y_{it-1} - \delta_{22}\ {}_2y_{it-1}\right), & \text{if } {}_2y_{it} = 0, \\ \left(-X_{it}^{(2)}\beta_{2i} - \delta_{21}\ {}_1y_{it-1} - \delta_{22}\ {}_2y_{it-1}, \infty\right), & \text{if } {}_2y_{it} = 1; \end{cases} \quad \text{for } {}_2\epsilon_{iS(i)}, \ldots,\ {}_2\epsilon_{iT(i)}.$$

The complete log likelihood is hence obtained as

$$\ell(gr;\theta) = \sum_{i=1}^{N} \log\left(L_i\right). \tag{3.16}$$

Since the likelihood contains integrals with up to fifty dimensions in the present application, an Efficient Importance Sampler based on the GHK procedure of Geweke et al. (1994), Hajivassiliou (1990), and Keane (1993, 1994) is used adapting the Sampler of Liesenfeld and Richard (2007) developed in the context of the multiperiod multinomial probit model. The corresponding estimate of the log likelihood is conceptually obtained as an average of the simulated likelihood contributions of country i

$$\tilde{\ell}(gr;\theta) = \sum_{i=1}^{N} \log \frac{1}{S} \sum_{s=1}^{S} \tilde{L}_i^{(s)}, \tag{3.17}$$

[8] A Bayesian estimation approach is computationally less convenient since, the identifying restrictions allow no direct sampling from the full conditional distributions of the parameters linked to the covariance matrix of errors $(e_{it},\ {}_1u_t,\ {}_2u_{it})'$ due to the imposed identifying restrictions.

[9] They prove that the behavior of estimators obtained form simulated maximum likelihood is asymptotically equivalent to maximum likelihood estimators.

where $\frac{1}{S}\sum_{s=1}^{S}\tilde{L}_i^{(s)}$ gives the numerical solution of the involved integral (Equation 3.15) based on S trajectories of parameters sampled from the constructed importance densities and $\tilde{L}_i^{(s)}$ denotes the integrand evaluated at the s^{th} draw from the importance densities. Since the moments of the employed importance densities are changing in the intercourse of optimization, the trajectories are all based on a common set of random numbers. Using Common Random Numbers (CRN) smoothes the likelihood function as all calculations are based on the same (small) numerical approximation error, which facilitates therefore the valid calculation of gradients and the Hessian matrix, see Pakes and Pollard (1989) and Danielsson and Richard (1995) for further details on this issue.[10]

The Efficient Importance Sampler is constructed in order to allow accurate computation of the involved integrals and therefore reduces the simulation error affecting parameter estimates to conventional levels. The incorporation of random coefficients within an Efficient Importance Sampler in the context of a treatment type model is new in the literature.[11] The sampler uses importance densities based on gaussian kernels and builds upon the Cholesky decomposition employed in the GHK-sampler, which is described in detail in Geweke and Keane (2001) in the context of the multinomial multiperiod probit model. The necessity to improve the GHK-procedure arises also, as documented in Geweke et al. (1997), from the serious bias in parameter estimates, especially, when high correlation is prevailing. Improvement of integration accuracy is achieved via the use of simple Least-Square optimizations, which transfer information concerning sampling moments in the likelihood structure ignored within the standard GHK procedure towards the sequentially employed importance sampling densities. The derivation of sampling moments, a full description of the integrating constants, the structure of the algorithm, and further technical details are given in Subsection 3.6.2 of this chapter. The appropriateness of the employed Efficient Importance Sampler is illustrated by a Monte Carlo Simulation in Subsection 3.6.3 of this chapter.

The next section gives the empirical results of the different models and discusses the determinants and costs of both types of crises.

3.4 Empirical Results

Within this section the estimation results for the different models are presented. The first subsection gives the results for the univariate model, while the second is concerned with the trivariate treatment model, where possible endogeneity of crises is controlled. The estimates are obtained as described above by Simulated Maximum Likelihood estimation and are based upon 500 draws. The Monte Carlo errors stemming from the numerical technique for solving the involved integrals are calculated using 20 different sets of common random numbers for estimation.

[10] Note that the Monte Carlo (MC) error stemming from the numerical solution of the integrals is then assessed via different sets of CRN's.

[11] Note that the implemented sampler is also suited to cover the multinomial multiperiod probit model with unobserved heterogeneity.

3.4.1 Linear Panel Model

The estimates of the panel model described in Equations (3.1) to (3.4) are given in Table (3.5). In order to test the hypotheses on the heterogeneous influence of both crises, three specifications allowing for various degrees of heterogeneity are considered. Specification I considers no heterogeneity for crises and no latent heterogeneity among the explaining variables of economic growth. The estimates reveal significant costs for both types of crises. The occurrence of a current account reversal reduces economic growth initially by 1.054 percentage points, while a currency crises leads to a contraction of output by 1.244 percentage points. The results are controlled for several typical macroeconomic variables considered as determinants of growth within the empirical literature. The financial development of a country is captured by the ratio of reserves to broad money. A low value proxies a more developed financial and banking sector of a country. The estimates indicate no significant influence of this variable. Also higher investment is significantly correlated with higher economic growth. Country specifics are captured by the variables life expectation and GDP per capita. Life expectation serves as a proxy for productivity and human capital. On the one hand higher GDP per capita also signals productivity, which can be expected to generate growth, on the other it proxies more generally the stage of development of a country, where classical theory suggests that less developed countries grow faster. Both variables have expected signs. Higher life expectancy enhances growth positively, while higher GDP per capita is related to lower growth, but only the effect of GDP per capita on growth is estimated significantly. Trade openness and lagged ratio of current account balance to GDP are included to control for the degree of international integration of an economy. Current account deficits and trade openness reflect access to international financial and world goods markets, what possibly enhances higher growth. Both variables have positive signs, although both are not significantly estimated at conventional levels. Also the global variables U.S. real interest rates and OECD growth rate show significant influence on economic growth. While higher U.S. real interest rates have negative influence on growth, OECD growth rates enhance growth. The positive influence of OECD growth on growth of the analyzed sample of merely developing and emerging markets can be explained via a higher demand for commodities, which constitute a large fraction of exports for these countries. The negative influence of US real interest rates may be based upon a rationing of international capital available for more risky investments in these countries.

Specifications II and III extend Specification I in order to test for heterogeneity within the influences of both types of crises. Specification II considers the interaction between both crises and a country's size measured by GDP per capita in 1984, as well as a country's trade openness. With respect to the interaction of country specifics with the influence of reversals, the findings suggest that larger countries suffer more from the occurrence of reversals and more openness can hinder a damaging effect. Both estimates are highly significant at the 1% level. The interaction between country specifics and the costs involved in currency crises is less clear. Again estimated coefficients point towards higher costs for larger economies and lower costs for more open economies, but neither coefficient is estimated significant. Although the three parameters capturing the effect of currency crises on economic growth are according to a LR test jointly significant, a test for joint significance of the two interaction terms of trade openness and country size with currency crises confirms the finding of both interactions being insignificant. Thus the results so far confirm the results presented by Edwards (2004) that the influence current account reversals exhibit on economic growth depends on the country specific characteristic of trade openness. Also the idea of Gupta et al. (2003) that larger countries experience more severe losses in output growth is confirmed, but only for reversals, while no systematic heterogenous influence is present for currency crises.

The next Specification III considers random coefficients within the explanatory variables of economic growth. This accounts for possible latent heterogeneity within the growth dynamics of a country. The results document a considerable degree of heterogeneity captured by the random coefficients with significant standard deviations for lagged economic growth, the level of reserves, and the US real interest rates. Specifying heterogeneity in this way allows for a country specific growth path characterized by specific dynamics and unconditional growth. The importance of country specific dynamics of growth, which is likely present due to institutional differences, has been emphasized by Lee et al. (1998). Two alternative specifications of the matrix Ω have been considered. The above results refer to a diagonal specification, and consequently to independent random coefficients. Results based on a fully specified covariance matrix (not reported here) reveal similar results. The documented costs of both types of crises as in Specification II are also present, when heterogeneity is incorporated within the growth equation. Model fitness for all three specifications is also assessed via adjusted coefficients of determination (adj. R^2). Calculation in case of random coefficients is based on expected β_i's, see subsection 4.5.5 of this chapter for details. The adjusted R^2 figures are given in the last row of Table (3.5) and show an increase from 0.208 to 0.348 in model fitness, when heterogeneity in costs and country specific growth dynamic are considered.

Summarizing, the results presented so far document heterogeneity for the influence of reversals, but possibly lack the control for endogeneity of both types of crises. Thus the next section presents the results for the trivariate treatment model.

3.4.2 Trivariate Panel Treatment Model

The estimation results concerning the Trivariate Treatment model incorporating serial correlation and heterogeneity in the sense of Specification III of the previous section are given in Table (3.6).[12] With respect to the determinants of both types of crises, an analysis based on a Bivariate Probit model provides similar results, which are given in Table (3.7).

Considered determinants of both crises are lagged current account deficits, money reserves ratio, investment, life expectation, lagged economic growth, trade openness, lagged crises indicators, and the global variables, US real interest rates and OECD growth rates. The estimates suggest that higher current account deficits significantly raise the probability of a current account reversal, while showing no significant influence on the occurrence probability of a currency crises. This finding is consistent with the analysis of current account sustainability, which has

[12] Thereby some insignificant random coefficients have not been considered further.

been triggered since the Mexican crisis in 1994, see Milesi-Ferretti and Razin (1996), and Ansari (2004). The results are also in line with those presented in Chapter 3. Global portfolio investment, as argued by Calvo (1998), may be more sensitive to shocks given already high deficits. Therefore, even smaller shocks are sufficient to render capital flows, thus enhancing current account reversals.

A higher ratio of broad money to international reserves significantly increases the probability of both types of crises.[13] This finding can be linked to theoretical issues. In typical models of balance of payment crises as in Flood and Garber (1984) and Obstfeld (1994), the crisis occurs when the stock of reserves is depleted. Hence, the higher the reserves, the later if at all, the crisis will occur.[14] As mentioned above this variable also proxies the stage of development of the financial institutions, where a lower money to reserves ratio captures less development. The results suggest that this channel seems less important in the context of crises or is dominated by the role of international reserves.

Life expectancy as a proxy of productivity is estimated significantly for both types of crises. Higher productivity may increase the export capabilities of a country. Its negative effect on the occurrence of currency crises might capture the stabilizing effect of a developed institutional background, which is also reflected in higher life expectancy. Although not significant, trade openness has a stabilizing effect on the occurrence of both types of crises, as a higher degree of trade openness allows a country to smooth domestic shocks. Investment, while also having no significant influence on the occurrence of currency crises, positively affects the probability of a current account reversal. Higher investment as argued by Blanchard (2006) strengthens a countries ability to pay of current account deficits via raising exports. GDP growth, while not significant for both types of crises, exhibits negative influence on the probability of both crises. Higher growth can be a signal of a sound macroeconomic environment, which decreases the probability of financial crises.

The global variables, US real interest rates and OECD growth rates, which capture the influence of the international business cycle on the occurrence of crises in the analyzed set of (mostly) developing countries, effect the probability of experiencing a reversal positive and are both significant at conventional levels. Such an influence is in line with the theoretical strand of literature, which argues that a shortening of external finance capabilities enhanced by a rise in safe interest rates and higher growth rates in more developed countries signaling investment opportunities, leads either to capital outflow or less inflow of capital, or both. In the context of current account reversals higher OECD growth rates may reflect higher exports of commodities, which is often a substantial fraction of export revenues for the analyzed countries. This channel has been emphasized by Obstfeld and Rogoff (2000), i.e. a current account reversal occurs to ensure the solvency of a country in face of shortened external finance. For currency crises

[13] Note that in the previous chapter, the influence of reserves are captured via the ratio of reserves to import, where higher reserves correspond to a higher value of the variable and hence influence negatively the probability of a reversal. In the above setting a higher stock of reserves causes ceteris paribus a lower ratio of broad money to reserves thus lowering the probability of a reversal.

[14] In other words, the lower the broad money to reserves ratio given a pegged exchange rate the longer can a central bank sustain its commitment to this particular exchange rate level.

only the global variable US real interest rate shows significant influence on the probability of a currency crises. One could argue along Hoffmaister and Vegh (1996) that countries vulnerable to currency crises often have a high degree of dollarization, which is an frequently observed phenomenon in high inflation periods. Hence a higher US interest rate possibly accelerates the money outflow and thus rises the probability of a currency crises.

The lagged binary indicators of both crises are included to capture possible state dependence. Both have significant influence on the probability of a current account reversal. As argued by Falcetti and Tudela (2006) state dependence occurs, when a past crisis has a structural effect on the economic constraints and behavior involved in crises. The positive effect of lagged currency crises, which is typically connected to a devaluation of the currency, seems to influence the trade and financial capabilities of a country, thus rising the probability of a current account reversal. Note that allowing the error structure to capture serial correlation hinders to assign state dependence spuriously to past crises. Current account reversals show significant negative influence on future reversals. For currency crises no influence is found of lagged current account reversals. This confirms the theoretical suggestion of Calvo and Mendoza (1996) that a currency crisis raises the probability of a balance of payments crisis. Past currency crises influence the probability of a crisis today negatively. One could argue that there is a kind of learning effect of economic agents (e.g. government) which renders the probability of a currency crash, but basically these results could as well reflect the depletion of international reserve hindering a renewed run on international assets.

Besides controlling for state dependence via the inclusion of lagged binary indicators, the model incorporates two other forms of serial dependence. Transitory serial dependence is incorporated via autocorrelated errors in order to assign state dependence not spuriously to lagged crises indicators. Persistent country specific heterogeneity stemming from unobserved factors is incorporated via random parameters. The correlation parameters for the two probit equations are all not estimated significantly. Thus implying that unobserved shocks are neither serially correlated nor correlated between equations. Country specific heterogeneity incorporated via random coefficients is assigned to both constants in order to incorporate a random effect, to the current account deficit for reversals, and to the level of reserves for currency crisis respectively. Only the lagged current account deficit exhibits heterogenous influence on the occurrence of current account reversals. This might reflect the observation that some countries provide investment opportunities, which are viewed as solid, thus causing no higher risk of a current account reversal.

The estimated effect of both types of crises on economic growth are given in the last column of Table (3.6). Taking the endogeneity of both types of crises into account alters the estimated costs of both types of crises. In order to test for significance of the covariance parameters governing the sample selection mechanism, univariate asymptotic t-tests are accompanied by LR-tests assessing the joint significance. Therefore the log likelihood value of the bivariate treatment model is compared to the sum of log likelihood values obtained from an estimation of a bivariate probit model and the estimated growth model. The estimated bivariate probit model is readily contained within the specification of the bivariate treatment model and allows to judge the determinants of both types of crises phenomena. Table (3.8) gives the log likelihood values for specifications allowing different degrees of serial correlation and heterogeneity. They are estimated jointly and separately, thus ignoring sample selection, in order to check for robustness. The first lines give the log likelihood value in the case, when no serial correlation and no heterogeneity is considered, while the next specification incorporates serial correlation. The third specification considers heterogeneity but no serial correlation, and finally, the last one considers heterogeneity and serial correlation. The corresponding LR test statistics indicate significance of all treatment specifications at the 1% level. The results suggest that only current account reversals are subject to a sample selection mechanism. The unobservable shocks of growth and reversals are positively correlated, such that neglecting this correlation leads to upward biased estimates.

Comparing the log likelihood values for the specifications incorporating latent country specific heterogeneity at different degrees reveals the significance of the considered heterogeneity structures. However, note that testing for random coefficients is non standard, since the variances of the random coefficients lie on the boundary of the parameter space. This violation of the standard regularity conditions causes the invalidity of the asymptotic χ^2-distribution of the LR statistic. Gourieoux et al. (1982) derive the correct asymptotic distribution as a mixture of χ^2-distributions.[15] The corresponding critical values are lower than those of a standard LR-test. Bearing this in mind assessing the significance of random coefficients via standard LR-tests provides a test with a significance level reaching at most the announced one, see also Harvey (1989). The estimates characterize the present heterogeneity as a random effect, heterogeneous growth dynamics, and heterogeneity within the influence of investment. Overall the numerical MC errors are sufficiently small in order to guarantee valid inference.

Cumulative Output Losses

The severity of both crises shall be assessed via computation of cumulative output losses involved in the occurrence of each type of crisis over time. The analyzed model framework providing a rich structure of intertemporal dependence provides a more realistic approximation to capture the influence of crises over time. Cumulated output losses are conceptualized as

$$E\left[\sum_{t=t_0}^{t^*} gr_{it}|\text{ crisis in } t_0\right] - E\left[\sum_{t=t_0}^{t^*} gr_{it}|\text{ no crisis in } t_0\right]. \tag{3.18}$$

These conditional expectations can be decomposed into

$$\begin{aligned} &E\left[\sum_{t=t_0}^{t^*} X_{it}\beta_i + \gamma_{1i}(\ _1y_{it}) + \gamma_{2i}(\ _2y_{it})|\text{ crisis in } t_0\right] + E\left[\sum_{t=t_0}^{t^*} e_{it}|\text{ crisis in } t_0\right] \\ &-E\left[\sum_{t=t_0}^{t^*} X_{it}\beta_i + \gamma_{1i}(\ _1y_{it}) + \gamma_{2i}(\ _2y_{it})|\text{ no crisis in } t_0\right] - E\left[\sum_{t=t_0}^{t^*} e_{it}|\text{ no crisis in } t_0\right]. \end{aligned} \tag{3.19}$$

[15] The asymptotic distribution for testing the significance of p random coefficients via a LR-test has the form $\sum_{i=0}^{p} w(p,i)\chi^2(i)$, where $w(p,i) = \frac{\binom{i}{p}}{2^p}$, $\chi^2(i)$ denotes a χ^2-distribution with i degrees of freedom and $\chi^2(0)$ the unit mass at the origin.

In order to provide a measure for average costs of crises, or in other words, the costs involved typically in the occurrence of crises for a country, the above given country specific expectations are assessed within a simulation study, where for the involved country specific regressors $\{X_{it}, X_{it}^{(1)}, X_{it}^{(2)}\}$ a profile is constructed aiming at a representation of a typical crises and non crises environment.[16] This profile is constructed as follows. In order to mimic the behavior of explaining variables in case of a typical crises in a representative manner, all crises episodes are monitored and the average for the variables is computed in the period of occurrence and the following periods. In case of no shock, the average is computed over the periods before the first crisis is observed. For the strict exogenous regressors capturing the state of global business cycle and world financial markets, two different scenarios are considered in order to capture a prosperous and a fragile state of the world economy. Scenario I is characterized with high OECD growth rates and high US real interest rates, where high interest and growth rates are measured as the 75% quantile of the rates observed over the period 1975 to 2004. Scenario II corresponds to a more fragile state of the world economy with low growth and interest rates set as the 25% quantiles of observed interest and growth rates. The expectations of errors are computed using a simulation. Therefore the errors and random coefficients are sampled from the corresponding distributions, see Subsection 4.5.4 of this chapter for details. The distribution of average costs are then obtained via producing 1000 trajectories of growth each of size 1000 for computation of the corresponding means.

The results are given in Table (3.9) and can be summarized as follows. Currency crises are less costly and cause only significant costs in the period of occurrence. Furthermore, the costs are higher when the world economy is in a favorable state. This reflects the opportunity costs of growth, i.e. growth would have been high in absence of a currency crises. The costs involved in a reversal are higher and are also significant in the period following the reversal episode. Profiles of growth given the occurrence of a crisis under the different considered global states are plotted in Figure (3.1). The estimated costs as delivered by the treatment model suggest a larger discrepancy than the cumulated output losses given in the bottom row of Table (3.9). This illustrates the raise in the occurrence probability of a reversal conditional on a currency crises occurred in the previous period. Thus neglecting the interdependence of both types of crises, see Chapter 3, causes an underestimation of involved costs. The results presented here are therefore at odds to those of Komarek and Melecky (2005) who report no direct effect of currency crises on economic growth and support the view of Milesi-Ferretti and Razin (2000) who report that currency crises are less distortive with respect to output performance than current account reversals. Both studies do not control for the possible endogeneity of both types of crises. Comparing the results concerning the costs of crises with those obtained in the analysis of Chapter 3 emphasizes the importance to consider structures incorporating latent country specific heterogeneity and serial dependence. In specific, a consideration of the joint influence of currency crises and current account reversals stresses the necessity to include currency crises as an important predictor of current account reversals in order to gauge correctly the economic

[16] Note that this approach also ensures in an ad hoc manner against reactions of the weak exogenous regressors, e.g. the ratio of reserves to broad money, on crises.

costs involved in crises connected to the balance of payments.

The two specifications presented here are consistent with the stylized facts discussed in the empirical literature on determinants of currency crises and current account reversals and their influence on economic growth. The estimation explicitly takes the endogeneity of both types of crises into account and documents higher costs for reversals when sample selection is considered.

3.5 Summary

Within this chapter the effects of macroeconomic crises such as currency crises and current account reversals on economic growth are analyzed. This chapter contributes an analysis allowing an explicit modeling of heterogeneity within the impact of crises. Furthermore, the possible endogeneity is controlled via a Treatment framework. Sources of serial dependence are incorporated within the model and estimation is performed based on a Simulated Maximum Likelihood approach. For accurate calculation of the involved integrals, an Efficient Importance Sampling scheme is developed and its performance is assessed. The results suggest a huge increase in integration accuracy, which allows to perform the required estimation properly. Using explaining variables discussed in the empirical literature on currency crises and current account reversals, two model specifications, one allowing to control for possible endogeneity, are used to capture the influence of both crises. The estimation results can be summarized as follows. Firstly, both types of crises have negative effects on economic growth in the period of occurrence. Secondly, while the effect of a reversal crisis is significantly depending on a country's size and openness, the effect of a currency crisis is not. Thirdly, significant heterogeneity prevails within the growth equation connected with the steady state level and growth dynamics captured via random coefficients. Fourthly, the estimation results of the Trivariate Treatment type model controlling for possible endogeneity suggest differences in the estimated costs of reversal crises on economic growth. Reversals are causing larger reductions in growth than currency crises. Accounting for endogeneity results in higher estimated costs as unobserved shocks are correlated for both equations explaining growth and the occurrence of current account reversals. Finally, currency crises serve as leading indicators of current account reversals. Hence, the analysis of Chapter 4 stresses the importance of a joint consideration of crises phenomena and extends hence the empirical analysis of current account reversal presented in Chapter 3.

An interesting expansion of analysis could be to assess the influence of both forms of crises via a nonparametric setting leaving the functional form unspecified. Nevertheless, this is beyond the scope of this chapter and left for future research.

Tab. 3.1: Listing of currency crises and reversal episodes and analyzed countries – (1)

	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986
Argentina	1 x	0 x	0 x	0 x	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Bangladesh	1 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Belize	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x
Bolivia	0 x	0 x	0 x	0 x	0 0	0 0	1 0	0 0	1 0	0 0	0 0	0 0
Botswana	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 1	1 0	0 0	0 0
Brazil	0 x	0 x	0 x	0 0	0 0	0 0	0 0	1 0	0 1	0 0	0 0	0 0
Burundi	0 x	1 x	0 x	0 x	0 x	0 x	0 x	0 x	1 x	0 x	0 x	1 x
Cameroon	0 x	0 x	0 x	0 x	0 x	0 0	0 0	1 0	0 0	1 0	0 0	0 0
Chile	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0
China, P.R.; Hong Kong	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0
Colombia	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	1 0	0 0
Costa Rica	0 x	0 x	0 x	0 x	0 x	0 0	1 0	0 1	0 0	0 0	0 0	0 0
Cyprus	0 x	0 x	0 x	0 x	0 0	0 0	0 1	0 0	0 0	0 0	0 1	0 0
Dominican Republic	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0	1 0	0 0
Ecuador	0 x	0 x	0 x	0 x	0 0	0 0	0 0	1 0	0 1	0 0	1 0	0 0
Egypt	0 x	0 x	0 x	0 x	1 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0
El Salvador	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 1	1 0
Equatorial Guinea	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x
Ethiopia	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0
Fiji	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 1	0 0	1 0
Ghana	0 x	0 x	0 x	1 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	1 0
Grenada	0 x	0 x	0 x	1 x	0 x	0 0	0 0	0 0	0 0	0 1	0 0	0 0
Guatemala	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Guinea-Bissau	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0
Guyana	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 1	0 0
Haiti	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0	0 0
Honduras	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0
Hungary	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0
India	0 x	1 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Indonesia	0 x	0 x	0 x	1 x	0 x	0 x	0 x	0 x	1 x	0 0	0 0	1 0
Jamaica	0 x	0 x	0 x	1 x	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 1
Jordan	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0
Kenya	1 x	0 x	0 x	0 0	0 0	0 0	1 0	0 1	0 0	0 0	1 0	0 0
Korea	0 x	0 x	0 x	0 x	0 0	1 0	0 0	0 1	0 0	0 0	0 1	0 0
Lao Peoples D.R.	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x
Madagascar	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 1	0 0	1 0	0 0	1 0
Malawi	0 x	0 x	0 x	0 x	0 x	0 0	0 0	1 1	0 0	0 0	1 0	0 0
Malaysia	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0	1 0
Mali	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Malta	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Mauritius	0 x	0 x	0 x	0 x	1 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0
Mexico	0 x	1 x	0 x	0 x	0 x	0 x	0 x	1 1	0 0	0 0	1 0	0 0
Morocco	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 1
Mozambique	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 1	0 0	0 0
Nepal	1 x	0 x	0 x	0 x	0 0	0 0	1 0	0 0	0 0	1 0	0 0	0 0
Nicaragua	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Nigeria	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 1	0 0	1 0
Pakistan	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Panama	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 1	0 0	0 0	0 0	0 0
Paraguay	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	1 0
Peru	0 x	1 x	0 x	0 x	1 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Philippines	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	1 0	0 1	0 1	1 0
Romania	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x	0 x
Sierra Leone	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 1	0 0	0 0	0 0
South Africa	1 0	0 0	0 1	1 0	0 0	0 0	0 0	0 0	0 0	1 0	0 1	0 0
Sri Lanka	0 x	0 x	1 x	0 0	0 0	0 0	0 0	0 0	0 1	0 0	0 0	0 0
Swaziland	1 x	0 x	0 0	0 0	1 0	0 0	0 0	1 0	0 0	1 0	0 1	0 0
Syrian Arab Republic	0 x	0 x	1 x	0 x	0 x	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Thailand	0 x	0 x	0 x	0 0	0 0	1 0	0 0	0 0	0 0	1 0	0 0	0 1
Trinidad & Tobago	0 x	0 x	0 x	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0
Tunisia	0 x	0 x	0 x	0 x	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 1
Turkey	0 x	0 x	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Uganda	0 x	0 x	0 x	0 x	0 x	0 x	1 x	0 x	0 0	0 0	0 0	0 0
Uruguay	0 x	0 x	0 x	0 x	0 x	0 x	0 0	1 1	0 0	0 0	0 0	0 0
Venezuela	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	1 0
Zambia	0 x	0 x	0 x	0 x	0 x	0 x	0 0	0 0	0 0	0 0	1 0	0 0
Zimbabwe	0 x	0 x	0 x	0 x	0 x	0 0	0 0	1 0	0 0	0 1	0 0	0 0

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the sequence refers to currency crises and reversals respectively.

Tab. 3.2: Listing of currency crises and reversal episodes and analyzed countries – (2)

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
Argentina	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Bangladesh	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Belize	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0	0 0
Bolivia	0 0	1 1	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0
Botswana	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0
Brazil	1 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0
Burundi	0 x	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Cameroon	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 x	0 x	0 x	0 x
Chile	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
China, P.R.; Hong Kong	0 0	0 0	0 0	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Colombia	0 0	0 0	0 0	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Costa Rica	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Cyprus	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0	0 0	0 0	0 0
Dominican Republic	1 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 1	0 0	0 0
Ecuador	0 0	1 0	0 0	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Egypt	0 1	0 0	1 0	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0
El Salvador	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Equatorial Guinea	0 x	0 x	0 x	0 0	1 0	0 1	0 0	1 0	0 x	0 x	0 x
Ethiopia	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0
Fiji	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1	0 0
Ghana	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Grenada	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Guatemala	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Guinea-Bissau	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	1 x	0 x
Guyana	1 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Haiti	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0
Honduras	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Hungary	0 0	0 0	1 0	0 1	0 0	0 0	0 0	1 0	0 0	0 0	0 0
India	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	1 0	0 0	0 0
Indonesia	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Jamaica	0 0	0 0	0 0	1 0	0 0	0 1	0 0	0 0	0 0	0 0	0 0
Jordan	1 0	0 0	1 0	0 0	0 0	1 0	0 0	0 1	0 0	0 0	0 1
Kenya	0 0	0 0	0 0	0 0	0 1	0 0	1 0	0 0	1 0	0 0	1 0
Korea	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Lao Peoples D.R.	0 0	0 0	0 0	0 1	0 0	0 0	0 0	0 0	1 0	0 0	0 0
Madagascar	0 0	0 0	0 0	0 0	1 0	0 0	0 0	1 0	0 0	0 0	0 0
Malawi	0 0	0 0	0 0	0 0	0 0	1 0	0 0	1 0	0 0	0 0	0 0
Malaysia	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Mali	0 0	0 0	0 1	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Malta	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	1 0
Mauritius	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Mexico	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 1	0 0	0 0
Morocco	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Mozambique	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	1 0	0 0	0 0
Nepal	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	1 0	0 0	0 0
Nicaragua	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Nigeria	0 0	0 0	1 1	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0
Pakistan	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Panama	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Paraguay	0 0	1 1	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0
Peru	1 0	0 0	0 1	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Philippines	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
Romania	0 x	0 x	0 x	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Sierra Leone	0 0	1 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0
South Africa	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0
Sri Lanka	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 1
Swaziland	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Syrian Arab Republic	0 1	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Thailand	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 1
Trinidad & Tobago	0 0	1 0	0 1	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Tunisia	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0	0 0
Turkey	0 0	0 0	0 0	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0
Uganda	1 0	0 0	1 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Uruguay	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
Venezuela	0 0	0 0	1 1	0 0	0 0	0 0	0 0	1 0	0 0	0 0	0 0
Zambia	0 0	0 0	0 0	0 0	0 0	0 1	0 0	1 0	0 0	0 0	0 0
Zimbabwe	0 0	0 0	0 0	0 0	1 0	0 0	0 x	1 x	0 x	0 x	1 x

Note: x refers to no observation available in period t, 0 indicates no reversal episode in period t; the sequence refers to currency crises and reversals respectively.

Tab. 3.3: Joint occurrence of currency crises and current account reversals

↓ currency crises, → reversals											
t, t				$t-1$,t				t,$t-1$			
	0	1	$\sum cr$		0	1	$\sum cr$		0	1	$\sum cr$
0	972	59	1031	0	924	51	975	0	911	58	975
1	122	8	130	1	106	13	119	1	119	6	119
$\sum rev$	1094	67	1161	$\sum rev$	1030	64	1094	$\sum rev$	1030	64	1094
$\chi^2 = 0.0395(0.8425)$				$\chi^2 = 6.2424(0.0125)$				$\chi^2 = 0.2825(0.5951)$			

Notes: The χ^2 test statistics follow a χ^2 distribution with one degree of freedom; p-values are given in parentheses; cr and rev refer to currency crises and current account reversals respectively.

Tab. 3.4: List of variables and summary statistics - Chapter 3

variable	frequency	data source	mean	sd
current account balance as % of GDP	annual	WDI	-4.2610	6.2851
GDP growth	annual	WDI	3.5739	4.9729
gross fixed investment as % of GDP	annual	WDI	22.3613	7.7402
trade openness	annual	WDI	65.8738	41.4010
annual OECD growth rates	annual	OECD	2.6922	1.3492
US real interest rates	annual	WDI	5.0311	2.4573
life expectancy at birth in total years in 1997	–	WDI	62.6982	11.1418
GDP per capita in 1984 (1000$)	–	WDI	1.6572	1.6297
money (M2) reserves ratio	annual	WDI	5.0392	52.6280
# observations		1161		
time period		1975-1997 (unbalanced)		

Tab. 3.5: Linear panel model of growth - Maximum likelihood estimation results

	I	*II*	*III*
con	-0.2371 (1.0675)	-0.2851 (1.0625)	0.0271 (1.0613)
growth $t-1$	0.5092^{**} (0.0667)	0.4826^{**} (0.0678)	0.2254^{**} (0.0931)
reserves	0.0014 (0.0028)	0.0013 (0.0027)	-0.0207^{*} (0.0114)
investment $t-1$	0.0503^{**} (0.0223)	0.0558^{**} (0.0268)	0.0273 (0.0338)
current account	0.0372 (0.0268)	0.0424 (0.0294)	0.2800 (0.3872)
trade openness	0.0520 (0.0367)	0.0379 (0.0443)	0.1000^{*} (0.0602)
σ_{con}	–	–	0.0010 (0.7192)
σ_{growth}	–	–	0.2175^{**} (0.0418)
σ_{reserves}	–	–	0.0331^{**} (0.0153)
$\sigma_{\text{investment}}$	–	–	0.0089 (0.0288)
$\sigma_{\text{current account}}$	–	–	0.0803 (0.4403)
$\sigma_{\text{trade openness}}$	–	–	0.0028 (0.0608)
US real interest rate	-0.1591^{*} (0.0889)	-0.1744^{**} (0.0838)	-0.2897^{**} (0.1016)
OECD growth rate	0.3011^{**} (0.1174)	0.3154^{**} (0.1129)	0.3531^{**} (0.1098)
$\sigma_{\text{US real int. rate}}$	–	–	0.1353^{**} (0.0584)
$\sigma_{\text{OECD growth}}$	–	–	0.0256 (0.1462)
life expectation	0.2054 (0.1706)	0.2092 (0.1699)	0.4698^{**} (0.2384)
GDP p.c. in 1000$ in 1984	-0.2180^{**} (0.1072)	-0.1303 (0.1156)	-0.3026^{*} (0.1628)
γ_1 – reversal	-1.0541^{*} (0.6152)	-1.6132 (1.2620)	-2.0651^{**} (1.0365)
GDP p.c. $\times$ reversal	–	-1.0328^{**} (0.3684)	-1.2558^{**} (0.3402)
trade $\times$ reversal	–	0.3634^{**} (0.1685)	0.4619^{**} (0.1484)
γ_2 – currency crisis	-1.2444^{**} (0.4438)	-0.5584 (1.0077)	-0.4538 (0.9790)
GDP p.c. $\times$ currency cr.	–	-0.4029 (0.2742)	-0.3095 (0.2480)
trade $\times$ currency cr.	–	0.0007 (0.1312)	-0.0037 (0.1160)
φ	-0.2652^{**} (0.0761)	-0.2352^{**} (0.0727)	0.0327 (0.1089)
σ	4.3358 (0.0973)	4.3107 (0.0975)	4.0466 (0.1015)
log likelihood	-3159.5	-3152.7	-3131.9
adj. R^2	0.208	0.216	0.348

Notes: Asymptotic standard errors are given in parentheses; ** denotes significance at the one sided 1% level; * denotes significance at the one sided 5% level.

Tab. 3.6: Trivariate panel treatment model - Simulated maximum likelihood estimation results

	reversal	MC	crises	MC	growth	MC
constant	-6.4498^{**} (0.8570)	0.0376	-0.9321^{**} (0.4109)	0.0043	0.4414 (1.0338)	0.1279
reserves	0.0104^{**} (0.0048)	0.0013	0.0077^{**} (0.0038)	0.0005	-0.0593^{**} (0.0168)	0.0122
investment	0.0204^{*} (0.0112)	0.0003	0.0037 (0.0088)	0.0001	0.0418 (0.0283)	0.0047
life expectation	0.3457^{**} (0.1060)	0.0047	-0.1072^{*} (0.0578)	0.0005	0.5082^{**} (0.2006)	0.0047
current account deficit	-0.1258^{**} (0.0224)	0.0011	-0.0056 (0.0091)	0.0001	0.0179 (0.0285)	0.0024
trade	-0.0237 (0.0217)	0.0004	-0.0218 (0.0145)	0.0002	0.0834 (0.0544)	0.0030
growth	-0.0259 (0.0179)	0.0015	-0.0127 (0.0108)	0.0002	0.1651^{**} (0.0765)	0.0001
lagged currency crises	0.3907^{**} (0.1759)	0.0013	-3.8014^{**} (1.0026)	0.3991	–	–
lagged reversal	-1.2302^{**} (0.4393)	0.0013	-0.2348 (0.2472)	0.0067	–	–
US real interest rates	0.1560^{**} (0.0499)	0.0005	0.0608^{*} (0.0333)	0.0003	-0.2507^{**} (0.0865)	0.0007
OECD growth rates	0.2258^{**} (0.0619)	0.0026	0.0561 (0.0433)	0.0002	0.4133^{**} (0.1067)	0.0025
GDP per capita	–	–	–	–	-0.2933^{*} (0.1528)	0.0052
currency crises	–	–	–	–	-0.3423 (1.9160)	0.0329
currency $\times$ GDP	–	–	–	–	-0.3642 (0.2363)	0.0089
currency crises $\times$ trade	–	–	–	–	0.0469 (0.1104)	0.0018
reversal	–	–	–	–	-6.2109^{**} (2.2533)	0.0069
reversal $\times$ GDP	–	–	–	–	-1.2038^{**} (0.3428)	0.0045
reversal $\times$ trade	–	–	–	–	0.4857^{**} (0.1739)	0.0064
σ_{con}	0.0001 (1.0632)	0.0002	0.0338 (0.1933)	0.0151	0.7973^{*} (0.3952)	0.2364
$\sigma_{\text{cad}}/\sigma_{\text{growth}}$	0.0658^{**} (0.0133)	0.0006	–	–	0.2303^{**} (0.0537)	0.0015
σ_{res}	–	–	0.0031 (0.0130)	0.0010	0.0350^{**} (0.0166)	0.0055
$\sigma_{\text{investment}}$	–	–	–	–	0.0135 (0.0204)	0.0084
$\sigma_{\text{US real int.}}$	–	–	–	–	0.0212 (0.1323)	0.0174
$\varphi_1/\varphi_2/\varphi$	-0.0213 (0.1145)	0.0156	0.1445 (0.1659)	0.0009	0.0942 (0.0784)	0.0032
$\psi_1/\psi_2/\rho$	0.5835^{**} (0.1507)	0.0060	0.0783 (0.1127)	0.0028	-0.0664 (0.1075)	0.0113
log likelihood/ adj. R^2 / σ	-3677.6	0.0571	0.367		4.1135 (0.1419)	0.0044

Notes: Asymptotic standard errors are given in parentheses; ** denotes significance at the one sided 1% level; * denotes significance at the one sided 5% level. Estimates are based on $S = 500$. MC errors are obtained via 20 independent replications.

Tab. 3.7: Bivariate panel probit model - Simulated maximum likelihood estimation results

	reversal	MC	crises	MC
constant	-6.3079^{**}	0.0103	-0.9169^{*}	0.0020
	(0.9873)		(0.4767)	
reserves	0.0134^{**}	0.0000	0.0074^{*}	0.0000
	(0.0059)		(0.0043)	
investment	0.0176	0.0001	0.0039	0.0000
	(0.0137)		(0.0092)	
life expectation	0.3171^{**}	0.0007	-0.1089^{*}	0.0001
	(0.1210)		(0.0647)	
current account deficit	-0.1264^{**}	0.0005	-0.0054	0.0000
	(0.0278)		(0.0097)	
trade	-0.0223	0.0001	-0.0216	0.0001
	(0.0263)		(0.0165)	
growth	-0.0277	0.0000	-0.0131	0.0000
	(0.0177)		(0.0118)	
US real interest rates	0.1673^{**}	0.0002	0.0594^{*}	0.0002
	(0.0553)		(0.0346)	
OECD growth rates	0.2078^{**}	0.0006	0.0558	0.0001
	(0.0677)		(0.0445)	
lagged currency crises	0.3690^{*}	0.0006	-4.8182^{**}	0.0043
	(0.2179)		(1.0004)	
lagged reversal	-1.3232^{**}	0.0079	-0.2231	0.0011
	(0.5791)		(0.2393)	
σ_{con}	0.0002	0.0027	0.0285	0.0056
	(1.0417)		(0.4404)	
$\sigma_{\mathrm{cad}}/\sigma_{\mathrm{res}}$	0.0606^{**}	0.0004	0.0001	0.0000
	(0.0177)		(0.0055)	
φ_1/φ_2	-0.1276	0.0030	0.1169	0.0009
	(0.1714)		(0.2532)	
ρ	-0.0467	0.0012		
	(0.1258)			
log likelihood	-557.2507	0.0571		
Pseudo R^2	0.119			

Notes: Asymptotic standard errors are given in parentheses; ** denotes significance at the one sided 1% level; * denotes significance at the one sided 5% level. Estimates are based on $S = 500$. MC errors are obtained via 20 independent replications.

Tab. 3.8: Model specification tests

	log likelihood		MC
pooled		-3716.0	0.0173
separate	-566.0+(-3157.4)	-3723.4	0.0189
LR-statistic		14.8***	
serial + no het.		-3711.2	0.0451
separate	-565.7+(-3152.7)	-3718.4	0.0233
LR-statistic		14.3***	
no serial + het.		-3678.1	0.0678
separate	-557.4+(-3132.6)	-3690.0	0.0435
LR-statistic		23.8***	
serial + het.		-3677.9	0.0660
separate	-557.4+(-3131.9)	-3689.3	0.0583
LR-statistic		22.8***	

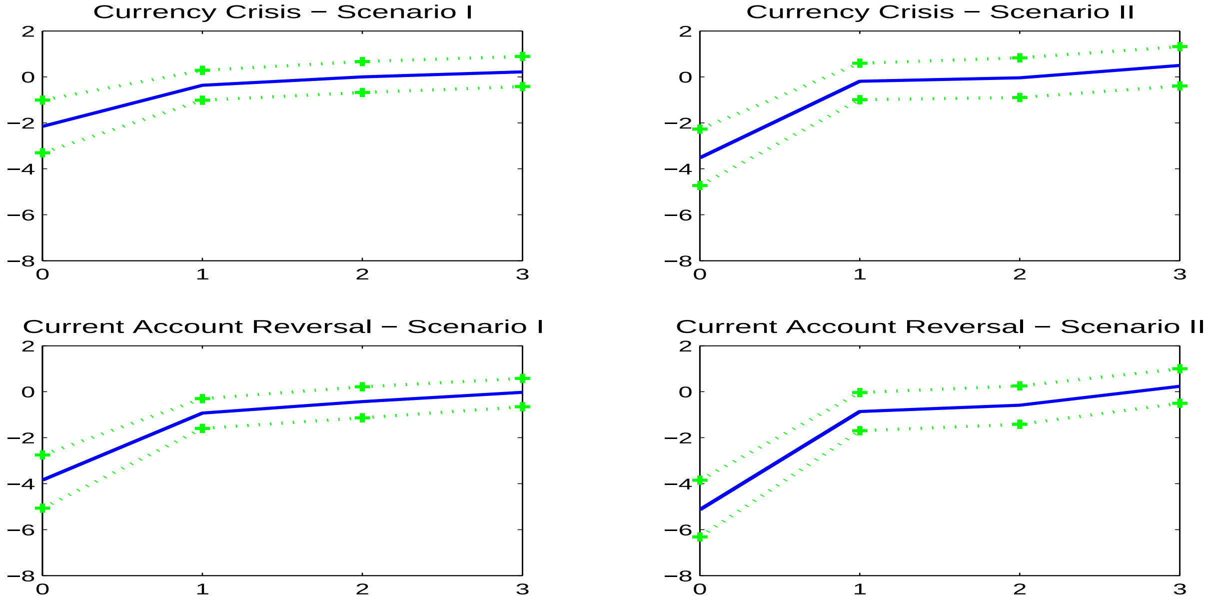
Notes: *** denotes significance at the one sided 1% level; ** denotes significance at the one sided 5% level; * denotes significance at the one sided 10% level. Estimates are based on $S = 500$. MC errors are obtained via 20 independent replications.

Tab. 3.9: Cumulated costs of crises

	currency crises I		currency crises II		reversal crises I		reversal crises II	
	Loss	95% CI	Loss	95% CI	Loss	95% CI	Loss	95%CI
$t=0$	-2.1508	$[-3.3038\ ;\ -1.0111]$	-3.5212	$[-4.7283\ ;\ -2.2701]$	-3.8455	$[-5.0670\ ;\ -2.7496]$	-5.1339	$[-6.3165\ ;\ -3.8486]$
$t=1$	-0.3627	$[-1.0134\ ;\ 0.2892]$	-0.1893	$[-0.9909\ ;\ 0.5974]$	-0.9314	$[-1.5952\ ;\ -0.3026]$	-0.8638	$[-1.6961\ ;\ -0.0352]$
$t=2$	0.0014	$[-0.6766\ ;\ 0.6672]$	-0.0392	$[-0.8980\ ;\ 0.8327]$	-0.4304	$[-1.1368\ ;\ 0.2170]$	-0.5849	$[-1.4189\ ;\ 0.2559]$
$t=3$	0.2186	$[-0.4223\ ;\ 0.8945]$	0.4977	$[-0.3907\ ;\ 1.3161]$	-0.0282	$[-0.6520\ ;\ 0.5797]$	0.2396	$[-0.5032\ ;\ 1.0009]$
$\sum$	-2.2935	$[-4.1768\ ;\ -0.3679]$	-3.2520	$[-5.3650\ ;\ -0.9758]$	-5.2354	$[-7.2941\ ;\ -3.3646]$	-6.3430	$[-8.6931\ ;\ -4.0541]$

Notes: Scenario I corresponds to high OECD growth rates and high US real interest rates; Scenario II corresponds to low OECD growth rates and low US real interest rates; the last row gives the cumulated output losses over 4 periods.

Fig. 3.1: Impact of crises on growth over time



Notes: Scenario I corresponds to high OECD growth rates and high US real interest rates; Scenario II corresponds to low OECD growth rates and low US real interest rates.

3.6 Technical Details

3.6.1 Integration of the Likelihood for the Linear Panel Model with Random Coefficients

The linear panel regression model with random coefficients modeling latent heterogeneity has been analyzed in the literature by Swamy (1970) discussing efficient estimation of the model parameters using generalized least squares estimators.[17] To retrieve the likelihood of the linear panel model with random coefficients described in Equations (3.1) - (3.3) in closed form, the corresponding integral has to be solved. With $e_i = gr_i - \overline{X}_i'\overline{\beta} - X_i\beta_i$ this integral is given as

$$\int\limits_{[\times(-\infty,\infty)]^k} (2\pi)^{-t_i/2}\det(\Sigma_i)^{-1/2}\exp\left\{-\frac{1}{2}e_i\prime\Sigma_i^{-1}e_i\right\}$$
$$\frac{1}{\sqrt{2\pi}}\det(\Omega)^{-0.5}\exp\{-\frac{1}{2}(\beta_i - b)\prime\Omega^{-1}(\beta_i - b)\}d\beta_i,$$

where k denotes the number of random coefficients and t_i denotes the number of periods observed for country i. The covariance matrix Σ_i describes the covariance of an moving average process of order one and is given by

$$\Sigma_i = \begin{pmatrix} \sigma^2 & \varphi\sigma^2 & 0 & \dots & & 0 \\ \varphi\sigma^2 & \sigma^2 & \varphi\sigma^2 & 0 & \dots & 0 \\ 0 & \ddots & \ddots & \ddots & & \vdots \\ \vdots & & & & \ddots & \varphi\sigma^2 \\ 0 & \dots & & 0 & \varphi\sigma^2 & \sigma^2 \end{pmatrix}. \tag{3.20}$$

The solution of the integral is based on the result that the product of two normal densities gives via rearrangement of quadratic forms, see Box and Tiao (1973), again a kernel of a normal density, such that the integrating constant is hence known analytically. In particular, the following steps are required. With $v_i = gr_i - \overline{X}_i'\overline{\beta}$ the integral expression can be rearranged as

$$\frac{(2\pi)^{-t_i/2}}{\det(\Sigma_i)^{1/2}} \int\limits_{[\times(-\infty,\infty)]^k} \exp\left\{-\frac{1}{2}\left((v_i - X_i\beta_i)'\Sigma_i^{-1}(v_i - X_i\beta_i) + (\beta_i - b)'\Omega^{-1}(\beta_i - b)\right)\right\}d\beta_i$$

$$= \frac{(2\pi)^{-\frac{t_i+k}{2}}\Xi_i}{\det(\Omega)^{1/2}\det(\Sigma_i)^{1/2}} \int\limits_{[\times(-\infty,\infty)]^k} \exp\left\{-\frac{1}{2}\left((\beta_i - \hat{\beta}_i)'\Psi_i(\beta_i - \hat{\beta}_i) + (\beta_i - b)'\Omega^{-1}(\beta_i - b)\right)\right\}d\beta_i,$$

where

$$\hat{\beta}_i = (X_i'\Sigma_i^{-1}X_i)^{-1}X_i'\Sigma_i^{-1}v_i, \quad \Psi_i = (X_i'\Sigma_i^{-1}X_i), \quad \text{and}$$
$$\Xi_i = \exp\left\{\frac{1}{2}\left(v_i'\Sigma_i^{-1}X_i\Psi^{-1}X_i'\Sigma_i^{-1}v_i - v_i'\Sigma_i^{-1}v_i\right)\right\}.$$

The above given quadratic forms in β_i can be simplified towards

$$\frac{(2\pi)^{-t_i/2-k/2}\Xi_i}{\det(\Omega)^{1/2}\det(\Sigma_i)^{1/2}}$$
$$\int\limits_{[\times(-\infty,\infty)]^k} \exp\{-\frac{1}{2}\left((\beta_i - \tilde{\beta})'(\Psi_i^{-1} + \Omega)^{-1}(\beta_i - \tilde{\beta}) + (\hat{\beta} - b)'(\Psi_i^{-1} + \Omega)^{-1}(\hat{\beta} - b)\right)\}d\beta_i,$$

[17] Note that Hildreth and Houck (1968) analyzed estimation of random coefficients in a time series context.

where $\tilde{\beta} = (\Psi_i^{-1} + \Omega)^{-1}(X_i'\Sigma_i^{-1}v_i + \Omega^{-1}b)$. Thus the solution is

$$(2\pi)^{-t_i/2}\det(\Psi_i^{-1}+\Omega)^{1/2}\det(\Omega)^{-1/2}\det(\Sigma_i)^{-1/2}\exp\{-\frac{1}{2}\Big((\hat{\beta}-b)'(\Psi_i^{-1}+\Omega)^{-1}(\hat{\beta}-b)\Big)\}\Xi_i.$$

Taking the product over all individuals (or summing the log over all individuals in case of the log likelihood) provides the (log) likelihood of the model.

3.6.2 Estimation of the Trivariate Treatment Model with Serial Correlation and Random Coefficients via an Efficient Importance Sampler

In the following, the principles of Efficient Importance Sampling shall be illustrated within two examples. The first example, given as a simplified version of the linear panel model with random coefficients considered above, is a pathological case fir importance sampling, but highlights some relevant issues for simulation based inference. The second example is a simple version of a mixed logit and aims to illustrate the use of auxiliary regressions, which allow to derive an importance density providing a global approximation of the integrand under consideration. General introductions to the use of simulation techniques in estimation are given in Geweke (1989), Richard (1995) and Stern (1997).

For the first example, let $N = 1$ and consider the absence of regressors except a random constant and no serial correlation within the error terms. To obtain the likelihood, the following integral has to be solved given as

$$I = \int_{-\infty}^{\infty}(2\pi)^{-1}\sigma^{-2}\exp\{-\frac{1}{2\sigma^2}\sum_{t=1}^{T}(gr_t-\beta)^2\}\frac{1}{\sqrt{2\pi\omega^2}}\exp\{-\frac{1}{2\omega^2}(\beta-b)^2\}. \tag{3.21}$$

In general the numerical solution of integration problems of the

$$I = E[g(x)] = \int g(x)f(x)dx,$$

where $f(x)$ is a proper density function can be obtained as

$$I \approx \tilde{I} = \frac{1}{S}\sum_{s=1}^{S} g(x^{(s)}),$$

where $x^{(s)}, s = 1,\ldots,S$ is a random sample from $f(x)$.[18] Hence, the solution of the integration problem given in (3.21) can be approximated as

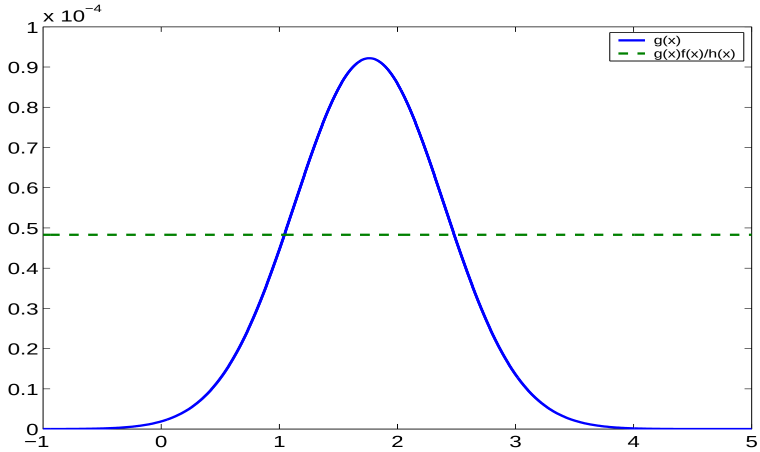
$$\tilde{I} = \frac{1}{S}\sum_{s=1}^{S}(2\pi)^{-1}\sigma^{-2}\exp\{-\frac{1}{2\sigma^2}\sum_{t=1}^{T}(gr_t-\beta^{(s)})^2\},$$

where $\beta^{(s)}, s = 1,\ldots,S$ constitute a random sample from $\mathcal{N}(b,\omega^2)$.

The corresponding numerical standard deviation $\sqrt{\frac{\mathrm{Var}[g(x)]}{S}}$ of the approximated solution of the integral decreases hence with rate $\sqrt{S}$. The numerical precision can therefore be increases to any desired level by an increase of the sample size of the random sample employed in calculation.

[18] The result follows directly from application of the strong law of large numbers.

Fig. 3.2: Illustration of importance sampling - 1



Notes: Behavior of $g(x)$ (– solid line) and $\frac{g(x)f(x)}{h(x)}$ (- - line) over the range of values for x.

Since the computation of the considered integral has be done many times, e.g. in the intercourse of maximization, even moderate sample size become in many applications computationally too expensive.[19] Hence methods are of special interest, which allow to obtain the same precision of calculation based on a smaller set of (common) random numbers. Efficient Importance Sampling is such an approach, since it is based on a more appropriate sampling density to obtain a random sample of $\beta^{(s)}, s = 1, \ldots, S$. More appropriate means that the sampling density provides a tighter (global) approximation of the integrand under consideration. Via providing a tighter approximation of the integrand it covers more efficiently the "important" regions necessary for an efficient calculation of the integral. Via the use of the importance density fulfilling the prerequisite to have the same support as $f(x)$, the integration problem is altered into

$$I = \int \frac{g(x)f(x)}{h(x)} h(x)dx,$$

where $h(x)$ denotes the properly chosen importance density. The numerical standard error of the approximation

$$\tilde{I} = \frac{1}{S}\sum_{s=1}^{S} \frac{g(x^{(s)})f(x^{(s)})}{h(x^{(s)})}$$

is thus reduced, since $h(x)$ is constructed to provide a better approximation of the integrand stressing thus the "important" regions of the integrand $g(x)f(x)$. The given Figure (3.2) illustrates the better approximation of a efficiently chosen sampling density. The solid line shows the variation of $g(x)$ for different values of x, while the dashed line illustrates the variation (in the present case no variation at all) of $\frac{g(x)f(x)}{h(x)}$ for different values of x.[20]

[19] Note that the repeated calculation of the integral within the maximization procedure is based on the same set of common random numbers (CRN). This smoothes the function to be maximized and allows hence the application of gradient based procedures.

[20] Note that only in pathological cases as the one considered above, where the analytical solution is known, a efficient importance density can be chosen, which allows to reduce the variation to zero. In normal settings only less variation than in the crude sampling approach can be achieved.

In the considered illustrative example, this more appropriate importance sampling density is given as a normal density with moments[21]

$$\mathcal{N}\left(\frac{\omega^2 \sum_{t=1}^{T} gr_t + b\sigma^2}{T\omega^2 + \sigma^2}, \frac{\omega^2\sigma^2}{T\omega^2 + \sigma^2}\right).$$

The following small simulation study illustrates the improved performance via the constructed importance density. For $T = 10$, $b = 2$ and $\omega = 10$ a β is sampled, which is used to generate $gr_1, \ldots, gr_{10}$ conditional on β with $\sigma^2 = 20$. The integral is solved 100 times for $S = \{1, 2, 5, 10, 20, 50, 100, 1000\}$ and means and mean squared errors are calculated from the 100 replications. The following Table (3.10) provides the results

Tab. 3.10: Simulation Study for illustration of efficient importance sampling - 1

$S \downarrow$	mean	MSE	mean	MSE
1	4.882e-005	3.388e-005	4.830e-005	0
2	4.925e-005	2.249e-005	–	–
5	4.864e-005	1.522e-005	–	–
10	4.834e-005	9.560e-006	–	–
20	4.761e-005	7.516e-006	–	–
50	4.813e-005	4.736e-006	–	–
100	4.875e-005	3.428e-006	–	–
1000	4.828e-005	1.062e-006	–	–

The results show that even very large sample sizes may not be sufficient to reduce the mean squared error in a way allowing correct evaluation of the considered integral.

Tab. 3.11: Simulation study for illustration of efficient importance sampling - 2

$S \downarrow$	mean	MSE	mean	MSE
5	0.492	0.088	0.499	0.003
10	0.498	0.061	0.500	0.003
20	0.500	0.043	0.500	0.002
50	0.503	0.030	0.500	0.001
100	0.496	0.021	0.500	0.001
1000	0.500	0.006	0.500	0.0002
5000	0.500	0.003	0.500	9.4994e-005

[21] These are obtained as follows. Since the integrand is proportional to

$$\begin{aligned}
I &\propto \exp\left\{-\frac{1}{2\sigma^2}\sum_{t=1}^{T}[\beta^2 - 2\beta gr_t + gr_t^2] - \frac{1}{2\omega^2}[\beta^2 - 2\beta b + b^2]\right\} \\
&\propto \exp\left\{-\frac{1}{2\sigma^2}[T\beta^2 - 2\beta\sum_{t=1}^{T} gr_t] - \frac{1}{2\omega^2}[\beta^2 - 2\beta b]\right\} \\
&\propto \exp\left\{-\frac{1}{2}[T\beta^2\omega^2 - 2\beta\sum_{t=1}^{T} gr_t\omega^2 + \beta^2\sigma^2 - 2\beta b\sigma^2]/(\omega^2\sigma^2)\right\} \\
&\propto \exp\left\{-\frac{T\omega^2 + \sigma^2}{2\omega^2\sigma^2}\left[\beta^2 - 2\beta\frac{\sum_{t=1}^{T} gr_t\omega^2 + b^2\sigma^2}{T\omega^2 + \sigma^2}\right]\right\},
\end{aligned}$$

which is the kernel of a normal distribution.

Since this first example is a pathological case, where by consideration of an importance sampling approach the simulation error can be reduced to zero, a second example is used to illustrate the efficiency gains linked to an efficient importance sampling approach. Consider the integral

$$I = \int_{-\infty}^{\infty} \frac{1}{1+e^x} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx,$$

with the corresponding straightforward numerical approximation

$$I \approx \tilde{I} = \sum_{s=1}^{S} \frac{1}{1+e^{x^{(s)}}},$$

where $x^{(s)}$ is a random sample from a standard normal distribution. Within this integral no importance density can be constructed via rearrangements of quadratic forms incorporating the full kernel of the integrand. However following Liesenfeld and Richard (2006), an importance density can be constructed as a global approximation to the integrand via solving least squares problems. Assuming that the importance density $m(x;a)$ belongs to a certain parametric class and depends hence on parameters a with kernel $k(x;a)$ and integrating constant $\chi(a)$ where $m(x;a) = \frac{k(x;a)}{\chi(a)}$. Since the efficient importance density aims at a tight global approximation of the integrand, it is linked to a minimization problem of the form

$$\min_{a_0,a} \int \left[\ln \phi(x) - a_0 - \ln k(x;a)\right]^2 w(x,a) m(x;a) dx$$

where $\phi(x) = g(x)f(x)$. This minimization problem states that via choosing a_0 and parameters $a \in A$ from the parameter space A of the parametric class of distributions $m(x;a)$, the weighted quadratic distance of the integrand $\chi(x) = g(x)f(x)$ from the kernel $k(x;a)$ with weights $w = \frac{\phi(x)}{m(x;a)}$ shall be minimized. Since the corresponding integral has in general no analytical solution, the corresponding (operational) Monte Carlo approximation of the form

$$\min_{a_0,a} \frac{1}{I} \sum_{i=1}^{I} \left[\ln \phi(x_i) - a_0 - \ln k(x_i;a)\right]^2 w(x_i;a)$$

is hence minimized, where where $x_i,\ i = 1 \rightarrow I$ represent a typical sample of random draws from the density used for approximation of the integral. In fact is shall represent a sample form the importance density $m(x;a)$ depending on a itself, which is not available at this stage. Therefore the procedure is iterated starting with an initial sample from e.g. the naive approach. Furthermore as noted by Richard and Zhang (2007), the weights $w(x;a)$ should be set to equal one in the first iterations to avoid numerical instability of the generalized least squares computations under large variance weights and the weights can be set to equal one in the following iterations, since as stated by Richard and Zhang (2007) the least squares form of the minimization problem is for most problems as accurate as the generalized least squares solution of the minimization problem. When the kernel $k(x;a)$ is assumed to belong to the exponential class of distributions, the kernel can be parameterized in a form that the corresponding minimization problem is linear with respect to the parameters a.[22] Computation of a (converging) sequence of auxiliary regressions yields finally the parameters a providing a global approximation of the integrand.[23]

For the considered example, an improved sampling density can be constructed, which incorporates an approximation to the term $\frac{1}{1+e^x}$. This is achieved as follows. Assuming that $k(x;a)$ corresponds to a Gaussian kernel, the following minimization problem is considered

$$\min_{a_0,a_1,a_2} \sum_{i=1}^{I} (-\ln(1+e^{x_i}) - a_0 - a_1 x_i - a_2 x_i^2)^2.$$

Starting with an initial sample $x_i,\ i = 1 \rightarrow I$ (say from the naive approach) the minimization problem is solved via least square regressions of the form

$$\hat{a} = (x'x)^{-1}x'y,$$

where

$$x = \begin{pmatrix} 1 & x_1 & x_1^2 \\ \vdots & \vdots & \vdots \\ 1 & x_I & x_I^2 \end{pmatrix} \text{ and } y = \begin{pmatrix} -\ln(1+e^{x_1}) \\ \vdots \\ -\ln(1+e^{x_I}) \end{pmatrix}.$$

Given a_1 and a_2, the importance density is characterized by the Gaussian kernel of the form

$$e^{a_1 x + a_2 x^2 - \frac{1}{2}x^2} = e^{-\frac{1}{2}(1-2a_2)[x^2 - 2x\frac{a_1}{1-2a_2}]},$$

corresponding to a normal density with moments $\mu = \frac{a_1}{1-2a_2}$ and $\sigma^2 = \frac{1}{1-2a_2}$. A sample is taken from this normal density and the minimization problem is solved again. Typically, fewer than 5 iterations are necessary to ensure convergence of the estimated parameters a_1 and a_2.

The results are given in Table (3.11) and indicate a reduction in simulation error by factor 20 to 30. Figure (3.3) illustrates the lower variation achieved via the importance density over a considerable range of x.

In order to obtain accurate estimates of the integral quantities involved within the likelihood given in Equation (3.16), an Efficient Importance Sampler based on the GHK-simulator introduced and discussed Börsch-Supan and Hajivassiliou (1993), and Geweke et al. (1994, 1997) is employed. The Efficient Importance Sampler (EIS) for the Bivariate Treatment Model with serially correlated errors and random coefficients is based on Liesenfeld and Richard (2007) who establish an EIS sampler for the multiperiod multinomial probit model with serial correlation within the error terms. In contrast to the multinomial probit model the lower bound for integration is not for all time periods given as $-\infty$. This asks for another handling of the integrating

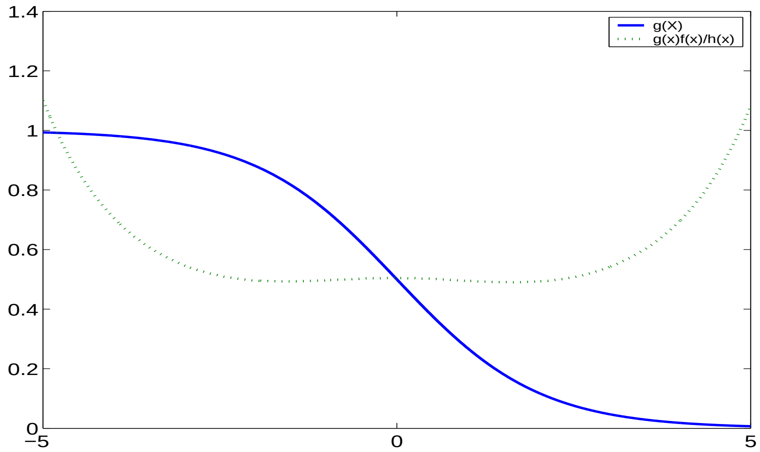
[22] The kernel of a density belonging to the exponential family has the form

$$\exp\left\{\sum_{j=1}^{J} g_j(\theta)c_j(x) + d(x)\right\},$$

where $g_j(\theta)$ are functions of the parameters of the density under consideration. Taking $\theta^* = \{g_1(\theta), \ldots, g_J(\theta)\}$ the log kernel is linear in θ^*.

[23] Convergence of the sequence of GLS estimates is based on a fixed point argument.

Fig. 3.3: Illustration of importance sampling - 2



Notes: Behavior of $g(x)$ (– solid line) and $\frac{g(x)f(x)}{h(x)}$ (- - line) over the range of values for x.

constant of the considered importance densities and for several refinements of the Efficient Importance Sampler in order to obtain an efficiency gain. The covariance structure of the model with serial correlation provides a setup in which not necessarily the nearest neighboring observation provides the most information about the sampling moments of the efficient sampler. Therefore, the integrating constant is ordered in such a way that each part containing only information from another time period is redirected to this very period. Importance Sampling based on the GHK procedure relies on proposal densities "which ignore critical information relative to the underlying correlation structure of the model under consideration, leading to potentially significant efficiency losses" (Liesenfeld and Richard (2007), p. 2). Efficiency improvements are achieved by simple Least-Squares approximations.

The construction on the Efficient Importance Sampler for the trivariate treatment model is in the following described in detail. Since the errors of the three model equations are assumed to be normally distributed the resulting joint distribution of all error components can be described in terms of a multivariate distribution conditionally on the random coefficients β_i, β_{1i} and β_{2i}

$$f_{e_{i\cdot},\epsilon_{1i\cdot},\epsilon_{2i\cdot}|\beta_i,\beta_{1i},\beta_{2i}}(e_{iS(i)},\ldots,e_{iT(i)},\epsilon_{1iS(i)},\ldots,\epsilon_{1iT(i)},\epsilon_{2iS(i)},\ldots,\epsilon_{2iT(i)}|\beta_i,\beta_{1i},\beta_{2i}),$$

with moments

$$\mu = \begin{pmatrix} O_{3(T(i)-D(i)+1)\times 1} \end{pmatrix} \quad \text{and} \quad \Sigma = \begin{pmatrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{13} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23} \\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33} \end{pmatrix},$$

where Σ_{11} denote the covariance structure of a MA(1) process given above in Equation (3.20), and Σ_{22} and Σ_{33} give the covariance matrix of an AR(1) process, each of dimension $t_i = T(i) -$

$S(i)+1$, i.e.

$$\Sigma_{ii} = \begin{pmatrix} \frac{1}{1-\varphi_i^2} & \frac{\varphi_i}{1-\varphi_i^2} & \cdots & \frac{\varphi_i^{T(i)-S(i)}}{1-\varphi_i^2} \\ \frac{\varphi_i}{1-\varphi_i^2} & \frac{1}{1-\varphi_i^2} & & \vdots \\ \vdots & & \ddots & \\ \frac{\varphi_i^{T(i)-S(i)}}{1-\varphi_i^2} & \cdots & & \frac{1}{1-\varphi_i^2} \end{pmatrix}, \quad i=\{2,3\}.$$

The matrices $\Sigma_{12}=\Sigma_{21}'$,$\Sigma_{13}=\Sigma_{31}'$, and $\Sigma_{23}=\Sigma_{32}'$ are given as

$$\Sigma_{12} = \begin{pmatrix} \psi_1(1+\varphi\varphi_1) & \psi_1(1+\varphi\varphi_1)\varphi_1 & \psi_1(1+\varphi\varphi_1)\varphi_1^2 & \cdots & \psi_1(1+\varphi\varphi_1)\varphi_1^{t_i-1} \\ \psi_1\varphi & \psi_1(1+\varphi\varphi_1) & \psi_1(1+\varphi\varphi_1)\varphi_1 & \cdots & \psi_1(1+\varphi\varphi_1)\varphi_1^{t_i-2} \\ 0 & \ddots & & \cdots & \vdots \\ \vdots & & & \psi_1(1+\varphi\varphi_1) & \psi_1(1+\varphi\varphi_1)\varphi_1 \\ 0 & \cdots & 0 & \psi_1\varphi & \psi_1(1+\varphi\varphi_1) \end{pmatrix},$$

$$\Sigma_{13} = \begin{pmatrix} \psi_2(1+\varphi\varphi_2) & \psi_2(1+\varphi\varphi_2)\varphi_2 & \psi_2(1+\varphi\varphi_2)\varphi_2^2 & \cdots & \psi_2(1+\varphi\varphi_2)\varphi_2^{t_i-1} \\ \psi_2\varphi & \psi_2(1+\varphi\varphi_2) & \psi_2(1+\varphi\varphi_2)\varphi_2 & \cdots & \psi_2(1+\varphi\varphi_2)\varphi_2^{t_i-2} \\ 0 & \ddots & & \cdots & \vdots \\ \vdots & & & \psi_2(1+\varphi\varphi_2) & \psi_2(1+\varphi\varphi_2)\varphi_2 \\ 0 & \cdots & 0 & \psi_2\varphi & \psi_2(1+\varphi\varphi_2) \end{pmatrix},$$

and

$$\Sigma_{23} = \frac{\rho}{1-\varphi_1\varphi_2} \begin{pmatrix} 1 & \varphi_1 & \varphi_1^2 & \cdots & \varphi_1^{t_i-1} \\ \varphi_2 & 1 & \varphi_1 & \cdots & \varphi_1^{t_i-2} \\ \varphi_2^2 & \ddots & 1 & \cdots & \vdots \\ \vdots & & & 1 & \varphi_1 \\ \varphi_2^{t_i-1} & \varphi_2^{t_i-2} & \cdots & \varphi_2 & 1 \end{pmatrix}.$$

These preliminaries allow to provide the connection between the joint distribution of error components conditional on the random coefficients and the likelihood function of a single panel member. Denote for ease of notation $\underline{\alpha}=(\beta_i,\beta_{1i},\beta_{2i})$. To derive the likelihood, the joint distribution of errors is then decomposed into

$$f_{\epsilon_{1i\cdot},\epsilon_{2i\cdot}|e_{i\cdot},\underline{\alpha}}(\epsilon_{1iS(i)},\ldots,\epsilon_{1iT(i)},\epsilon_{2iS(i)},\ldots,\epsilon_{2iT(i)}|e_{iS(i)},\ldots,e_{iT(i)},\underline{\alpha})\cdot$$
$$f_{e_{i\cdot}|\underline{\alpha}}(e_{iS(i)},\ldots,e_{iT(i)}|\underline{\alpha}),$$

where the moments of the conditional distribution are from multivariate normal theory[24]

$$\mu_c = \begin{pmatrix} \Sigma_{21} \\ \Sigma_{32} \end{pmatrix} \Sigma_{11}^{-1} e_{i\cdot} \quad \text{and} \quad \Sigma_c = \begin{pmatrix} \Sigma_{22} & \Sigma_{23} \\ \Sigma_{32} & \Sigma_{33} \end{pmatrix} - \begin{pmatrix} \Sigma_{21} \\ \Sigma_{32} \end{pmatrix} \Sigma_{11}^{-1} \begin{pmatrix} \Sigma_{12} & \Sigma_{23} \end{pmatrix}.$$

[24] see Mittelhammer (1996) and Bolch and Huang (1974) for a discussion of the concepts involved in the derivation of conditional distributions from multivariate normal setups.

Integrating the conditional distribution over the range

$$R_{1,it} = \begin{cases} \left(-\infty, -X_{it}^{(1)}\beta_{1i} - \delta_{11}\ {}_1y_{it-1} - \delta_{12}\ {}_2y_{it-1}\right), & \text{if } {}_1y_{it} = 0, \\ \left(-X_{it}^{(1)}\beta_{1i} - \delta_{11}\ {}_1y_{it-1} - \delta_{12}\ {}_2y_{it-1}, \infty\right), & \text{if } {}_1y_{it} = 1; \end{cases} \quad \text{for } {}_1\epsilon_{iS(i)}, \ldots, {}_1\epsilon_{iT(i)},$$

$$R_{2,it} = \begin{cases} \left(-\infty, -X_{it}^{(2)}\beta_{2i} - \delta_{21}\ {}_1y_{it-1} - \delta_{22}\ {}_2y_{it-1}\right), & \text{if } {}_2y_{it} = 0, \\ \left(-X_{it}^{(2)}\beta_{2i} - \delta_{21}\ {}_1y_{it-1} - \delta_{22}\ {}_2y_{it-1}, \infty\right), & \text{if } {}_2y_{it} = 1; \end{cases} \quad \text{for } {}_2\epsilon_{iS(i)}, \ldots, {}_2\epsilon_{iT(i)},$$

delivers conditional on the randomized parameters the probability for the observed sequences of current account reversals and currency crises, i.e.

$$\Pr(\ {}_1y_{iS(i)}, \ldots,\ {}_1y_{iT(i)},\ {}_2y_{iS(i)}, \ldots,\ {}_2y_{iT(i)}|\underline{\alpha}) =$$
$$\iiint\limits_{R_{1,iS(i)}\cdots R_{1iT(i)}R_{2,iS(i)}\cdots R_{2,iT(i)}} f_{\epsilon_{1i\cdot},\epsilon_{2i\cdot}|e_{i\cdot},\underline{\alpha}}(\epsilon_{1i\cdot},\epsilon_{2i\cdot}|e_{i\cdot},\underline{\alpha})d\epsilon_{1iS(i)}\ldots d\epsilon_{1iT(i)}d\epsilon_{2iS(i)}\ldots d\epsilon_{2iT(i)}.$$

Note that not necessarily all parameter within the probit equations have to be assigned a random coefficient. In this case $X_{it}^{(2)}\beta_{2i}$ changes into $\overline{X}_{it}^{(1)}\overline{\beta}_1 + X_{it}^{\text{ran}(1)}\beta_{1i}$ and $X_{it}^{(2)}\beta_{2i}$ into $\overline{X}_{it}^{(2)}\overline{\beta}_2 + X_{it}^{\text{ran}(2)}\beta_{2i}$. This integral of dimension $2t_i$ (in present context $2t_i \approx 40$ has to approximated using simulation techniques, since numerical integration methods such as quadrature procedures fail for this high dimension.

The incorporation of the observed growth rates is conducted via the observation that the marginal distribution of growth rates $gr_{i\cdot}$,

$$f_{gr_{i\cdot}|\underline{\alpha}}(gr_{iS(i)}, \ldots, gr_{iT(i)}|\underline{\alpha})$$

corresponds to $f_{e_{i\cdot}|\underline{\alpha}}(\cdot)$ evaluated at $e_{i\cdot} = gr_{i\cdot} - \overline{X}_{i\cdot}\overline{\beta} - X_{i\cdot}^{\text{ran}}\beta_i - \gamma_1(\cdot) - \gamma_2(\cdot)$ in case not all parameters of the growth equation are considered to be random parameters. Accordingly $f_{\epsilon_{1i\cdot}\epsilon_{2i\cdot}|gr_{i\cdot},\underline{\alpha}}(\cdot)$ corresponds to $f_{\epsilon_{1i\cdot}\epsilon_{2i\cdot}|e_{i\cdot},\underline{\alpha}}(\cdot)$ evaluated at $e_{i\cdot} = gr_{i\cdot} - \overline{X}_{i\cdot}\overline{\beta} - X_{i\cdot}^{\text{ran}}\beta_i - \gamma_1(\cdot) - \gamma_2(\cdot)$. The likelihood for country i can be rewritten as

$$L_i = \int\limits_{(-\infty,\infty)^{k+k_1+k_2}} \iiint\limits_{R_{1,iS(i)}\cdots R_{1iT(i)}R_{2,iS(i)}\cdots R_{2,iT(i)}} f_{\epsilon_{1i\cdot}\epsilon_{2i\cdot}|gr_{i\cdot},\underline{\alpha}}(\cdot)d\epsilon_{1i\cdot}d\epsilon_{2i\cdot}f_{gr_{i\cdot}|\underline{\alpha}}(\cdot)f_{\underline{\alpha}}(\underline{\alpha})d\underline{\alpha}, \quad (3.22)$$

where k, k_1, k_2 denote the size of β_i, β_{1i} and β_{2i} and $f_{\underline{\alpha}}(\underline{\alpha})$ the joint distribution of random parameters respectively.[25]

Given these preliminaries, the integration problem can be rephrased employing the Cholesky factorization of the covariance matrix. Rephrasing the structure of the integral in terms of the

[25] Note that the suggested order of integration is arbitrarily chosen in the sense that a simple reordering, i.e.

$$d\epsilon_{i1S(i)}d\epsilon_{i2S(i)}d\epsilon_{i1S(i)+1}d\epsilon_{i2S(i)+1}\ldots d\epsilon_{i1T(i)-1}d\epsilon_{i2T(i)-1}d\epsilon_{i1T(i)}d\epsilon_{i2T(i)}$$

instead of

$$d\epsilon_{i1S(i)}d\epsilon_{i1S(i)+1}\ldots d\epsilon_{i2T(i)-1}d\epsilon_{i2T(i)}$$

with the corresponding changes in the moments of the underlying normal distribution would provide the same results.

Cholesky decomposition simplifies the structure of the integrand and allows more easily the construction of an Efficient Importance Sampler. The considered integral gives the likelihood contribution of the ith panel member. For ease of notation indices referring to individual i are dropped. With $\underline{x} = (\epsilon_{1S(i)}, \ldots, \epsilon_{1T(i)}, \epsilon_{2S(i)}, \ldots, \epsilon_{2T(i)})$ and $\underline{\eta} = (\underline{x}, \underline{\alpha})$ it is given as

$$L = \int_{[\times(-\infty,\infty)]^{k+k_1+k_2+2t_i}} \prod_{t=1}^{2t_i} D_t \phi(x_t) d\underline{x} f_{gr|\underline{\alpha}}(gr|\underline{\alpha}) f_{\underline{\alpha}}(\underline{\alpha}) d\underline{\alpha}$$

where k, k_1 and k_2 denote the number of random coefficients in the growth and probit Equations 1 and 2 respectively, $\phi(\cdot)$ denotes the density of a standard normal distribution, $f_{gr|\underline{\alpha}}(gr|\underline{\alpha})$ denotes the distribution of observed growth rates conditional on the random coefficients, $f_{\underline{\alpha}}(\underline{\alpha})$ denotes the joint unconditional distribution of the random effects, and the range of integration is given as

$$D_t = I\left[\left(\frac{-\mu_t - H_t\underline{\alpha} - C_{t,1:t-1}\underline{x}_{t-1}}{C_{t,t}}, \infty\right)^{y_{it}} \left(-\infty, \frac{-\mu_t - H_t\underline{\alpha} - C_{t,1:t-1}\underline{x}_{t-1}}{C_{t,t}}\right)^{1-y_{it}}\right],$$

where C refers to the Cholesky decomposition of the Σ^c,

$$\mu = \begin{pmatrix} \overline{X}_1\overline{\beta}_1 + \delta_{11}\ {}_1y_{-t} + \delta_{12}\ {}_2y_{-t} \\ \overline{X}_2\overline{\beta}_2 + \delta_{21}\ {}_1y_{-t} + \delta_{22}\ {}_2y_{-t} \end{pmatrix} - \begin{pmatrix} \Sigma_{12} \\ \Sigma_{32} \end{pmatrix} \Sigma_{11}^{-1}(gr - \overline{X\beta} - \gamma_1(\cdot) - \gamma_2(\cdot)),$$

with ${}_jy_{-t}$, $j = \{1, 2\}$ referring to lagged crises indicators and

$$H = -\begin{pmatrix} \Sigma_{21}\Sigma_{11}^{-1}X^{\text{ran}} & X_1^{\text{ran}} & 0 \\ \Sigma_{32}\Sigma_{11}^{-1}X^{\text{ran}} & 0 & X_2^{\text{ran}} \end{pmatrix}.$$

The importance sampling densities are introduced as follows

$$\int_{[\times(-\infty,\infty)]^{k+k_1+k_2+2t_i}} \frac{D_{2t_i}\phi(x_{2t_i})}{k_{2t_i}(\underline{\eta}_{2t_i})} \prod_{t=2}^{2t_i-1} \frac{\chi_{t+1}(\underline{\eta}_t) D_t \phi(x_{t-1})}{k_t(\underline{\eta}_{t-1})} \frac{\chi_2(\underline{\eta}_1) D_1 \phi(x_1)}{k_1(\underline{\eta}_1)}$$
$$\frac{\chi_1(\underline{\alpha}) f_{gr|\underline{\alpha}}(gr|\underline{\alpha}) f_{\underline{\alpha}}(\underline{\alpha})}{m_0(\underline{\alpha})} \prod_{t=2}^{2t_i} m_t(x_i|\underline{x}_{i-1}, \underline{\alpha}) m_1(x_1|\underline{\alpha}) m_0(\underline{\alpha}) d\underline{x} d\underline{\alpha},$$

where $m_t(x_t|\underline{\eta}_{t-1})$ denotes the conditional density of x_t given $\underline{\eta}_{t-1}$ derived out of $k_t(\underline{x}_t)/\chi_t(\underline{\eta}_t)$.

A particular choice for the importance density is to set $\frac{k_t(\underline{\eta}_t)}{\chi(\underline{\eta}_t)} = \frac{\phi(x_t)}{\Phi(u_t) - \Phi(l_t)}$, where u_t and l_t are the indicated upper and lower bounds of the range D_t given above. This specific choice of the importance density provides the GHK simulator of Geweke et al. (1994, 1997), Börsch-Supan and Hajivassiliou (1993), and Keane (1993,1994). The GHK simulator is used as initial sampler for the auxiliary regressions solving the necessary minimization problem for construction of the efficient importance density. The resulting numerical approximation of the integral is given by

$$\frac{1}{S}\sum_{s=1}^{S}\prod_{t=1}^{2t_i}\left[\Phi(u_t^{(s)}) - \Phi(l_t^{(s)})\right] f_{gr|\underline{\alpha}}(gr|\underline{\alpha}^{(s)}),$$

where $\underline{\alpha}^{(s)}$ are sampled from $f_{\underline{\alpha}}(\underline{\alpha})$. As Greene (2004,b) noted the GHK simulator lacks numerical precision for a number of period exceeding 10. Also it lacks a comprehensive consideration of the random coefficients representing latent country specific heterogeneity. These issues are addressed via the construction of an efficient importance sampling approach, which is outlined below.

For construction of an efficient importance density the task is to find the moments of $m_t(\cdot)$ and forms of the integrating constants $\chi_t(\cdot)$ and kernels $k_t(\cdot)$ such that the closest possible fitting of the importance density is obtained. With respect to the importance density of the random effects the density is chosen in order to match the integrating constant left from the integration of the errors best. Note that parts of the integrating constants for the errors only depend on the random effects and are hence directly incorporated in $m_0(\cdot)$. The following paragraph will explicitly state the forms of all integrating constants and the conditional moments of the efficient importance density. Note that the construction of the moments of the efficient importance densities is iteratively. As an initial sampler the GHK simulator given above is used. In the present application three iterations through the auxiliary regressions have been found sufficient to guarantee convergence of the parameters constituting the moments of the efficient importance densities.

In general the following form for $k_t(\cdot)$ shall be considered

$$k_t(\underline{\eta}_t) = \frac{1}{\sqrt{2\pi}} D_t \exp\left\{-\frac{1}{2}\left[\underline{\eta}_t\prime P_t \underline{\eta}_t - 2\underline{\eta}_t\prime q_t + r_t\right]\right\}. \tag{3.23}$$

The forms of P_t, q_t and r_t and the corresponding values of $\chi_t(\cdot)$ have to be considered for each period recursively. Furthermore, define for notational convenience

$$\begin{aligned}
a_{t-1} &= \frac{\frac{-\mu_t}{C_{t,t}} - \mu^c_{1t}}{\sigma^c_t}, \\
h_{t-1} &= \frac{\frac{-H_t}{C_{t,t}} - \mu^c_{2t}}{\sigma^c_t}, \\
b_{t-1} &= \frac{\frac{-C_{t,1:t-1}}{C_{t,t}} - \mu^c_{3t}}{\sigma^c_t}, \\
\delta_t &= 1 - 2y_t, \\
\omega_t(\underline{\eta}_t) = \omega_t &= (a_t + h_t\underline{\alpha} + b_t\underline{x}_t),
\end{aligned}$$

where μ^c_{1t}, μ^c_{2t} and μ^c_{3t} are parts of the conditional mean μ^c_t and σ^c_t denotes the conditional moments of the conditional sampling densities for x_t. Note that given this notation the integrating constant takes the general form

$$\chi_t(\underline{\eta}_{t-1}) = \sigma^c_t \Phi(\delta_t \omega_{t-1}) \exp -\frac{1}{2}[\underline{\eta}_{t-1}\prime P^*_{t-1}\underline{\eta}_{t-1} - 2\underline{\eta}_{t-1}\prime q^*_{t-1} + r^*_{t-1}].$$

The specific evolution of the integrating constants and the conditional moments are obtained via a backward recursion.

Period $2t_i$: $k_{2t_i}(\cdot)$ is chosen such that a close match to $D_{2t_i}\phi(x_{2t_i})$ is achieved. In this case perfect fit can be achieved by setting

$$\begin{aligned}
P_{2t_i} &= e_{2t_i}e'_{2t_i}, \quad e_{2t_i} = (0,0,\ldots,0,1)' \text{ where } \dim(e_{2t_i}) = 1 \times 2t_i + k + k_1 + k_2, \\
q_{2t_i} &= (0,\ldots,0)' \text{ where } \dim(e_{2t_i}) = 1 \times 2t_i + k + k_1 + k_2, \\
r_{2t_i} &= 0.
\end{aligned}$$

This choice results in $\mu^c_{2t_i} = 0$, with $\mu_{1,2t_i} = 0$, $\mu_{2,2t_i} = \begin{pmatrix} 0 & 0 \end{pmatrix}$, $\mu_{3,2t_i} = \begin{pmatrix} 0 & \ldots & 0 \end{pmatrix}$, with $\dim(\mu_{3,2t_i}) = 1 \times 2t_i - 1$ and $\sigma^c_{2t_i} = 1$ and provides the corresponding integrating constant given as

$$\chi_{2t_i}(\underline{\eta}_{2t_i-1}, \underline{\alpha}) = \Phi\left(\delta_{2t_i} w_{2t_i-1}\right).$$

Note that in period $2t_i$ no part of the integrating constant can be isolated to depend solemnly on the random effects. This will be different in the following periods.

Period $2t_i - 1$: $k_{2t_i-1}(\cdot)$ is chosen to match $\chi_{2t_i}(\underline{\eta}_{2t_i-1}) D_{2t_i-1}\phi(x_{2t_i-1})$. Key part is to set the kernel $k_{2t_i-1}(\underline{\eta}_{2t_i-1})$ equal to

$$k_{2t_i-1}(\underline{\eta}_{2t_i-1}) = \frac{1}{\sqrt{2\pi}} D_{2t_i-1} \exp\left\{-\frac{1}{2}\left[x^2_{2t_i-1} + \hat{\alpha}_{2t_i-1}\omega^2_{2t_i-1} - 2\hat{\beta}_{2t_i-1}\omega_{2t_i-1}\right]\right\},$$

where $\hat{\alpha}_{2t_i-1}$ and $\hat{\beta}_{2t_i-1}$ are obtained from the regression

$$\log\left(\Phi(\delta_{2t_i}\omega_{2t_i-1})\right) = \tilde{c}_0 + \tilde{c}_1\omega_{2t_i-1} + \tilde{c}_2\omega^2_{2t_i-1},$$

with $\tilde{c}_1 = \hat{\beta}_{2t_i-1}$ and $\tilde{c}_2 = -\frac{1}{2}\hat{\alpha}_{2t_i-1}$. This choice for $k_{2t_i-1}(\underline{\eta}_{2t_i-1})$ can be represented in the form given in Equation (3.23) by setting

$$\begin{aligned}
P_{2t_i-1} &= e_{2t_i-1}e'_{2t_i-1} + \hat{\alpha}_{2t_i-1}\begin{pmatrix} h'_{2t_i-1} \\ b'_{2t_i-1} \end{pmatrix}\begin{pmatrix} h_{2t_i-1} & b_{2t_i-1} \end{pmatrix}, \\
&\text{with} \quad e_{2t_i-1} = (0,\ldots,0,1)' \text{ and } \dim(e_{2t_i-1}) = 1 \times 2t_i - 1 + k + k_1 + k_2, \\
q_{2t_i-1} &= \left[(\hat{\beta}_{2t_i-1} - \hat{\alpha}_{2t_i-1}a_t)\begin{pmatrix} h'_{2t_i-1} \\ b'_{2t_i-1} \end{pmatrix}\right] \\
r_{2t_i-1} &= \hat{\alpha}_{2t_i-1}(a_{2t_i-1})^2 - 2\hat{\beta}_{2t_i-1}(a_{2t_i-1}).
\end{aligned}$$

Given this form for $k_{2t_i-1}(\underline{\eta}_{2t_i-1})$ the integrating constant is obtained via

$$\begin{aligned}
\chi_{2t_i-1}(\underline{\eta}_{2t_i-2}) &= \int D_{2t_i-1}k_{2t_i-1}(\underline{\eta}_{2t_i-1})dx_{2t_i-1} \\
&= \Phi\left(\delta_{2t_i-1}\omega_{2t_i-2}\right) \\
&\quad \exp\left\{-\frac{1}{2}\left[\underline{\eta}'_{2t_i-2}P^*_{2t_i-2}\underline{\eta}_{2t_i-2} - 2\underline{\eta}_{2t_i-2}{}'q^*_{2t_i-2} + r^*_{2t_i-2}\right]\right\}
\end{aligned} \tag{3.24}$$

with

$$\begin{aligned} P^*_{2t_i-2} &= P^I_{2t_i-1} - \frac{P^{III}_{2t_i-1}{}' P^{III}_{2t_i-1}}{P^{II}_{2t_i-1}}, \\ q^*_{2t_i-2} &= q^I_{2t_i-1} - \frac{q^{II}_{2t_i-1} P^{III}_{2t_i-1}}{P^{II}_{2t_i-1}}, \\ r^*_{2t_i-2} &= r_{2t_i-1} - \left(\frac{q^{II}_{2t_i-1}}{\sqrt{P^{II}_{2t_i-1}}} \right)^2 + \log(P^{II}_{2t_i-1}), \end{aligned}$$

Superscripts I, II, and III refer to partitions of the matrices P_t and q_t given as

$$P_t = \begin{pmatrix} P^I_t & P^{III}_t{}' \\ P^{III}_t & P^{II}_t \end{pmatrix}, \quad q_t = \begin{pmatrix} q^I_t \\ q^{II}_t \end{pmatrix}.$$

Within the integration performed in Equation (3.24), the conditional moments used for sampling of x_{2t_i-1} are identified as

$$\mu^c_{2t_i-1} = \frac{q^{II}_{2t_i-1} - P^{III}_{2t_i-1}\underline{\eta}_{2t_i-2}}{P^{II}_{2t_i-1}} \quad \text{and} \quad \sigma^c_{2t_i-1} = \frac{1}{\sqrt{P^{II}_{2t_i-1}}},$$

where

$$\begin{aligned} \mu^c_{2t_i-1} &= \frac{q^{II}_{2t_i-1} - P^{III}_{2t_i-1}\underline{\eta}_{2t_i-2}}{P^{II}_{2t_i-1}} \\ &= \frac{q^{II}_{\mu,2t_i-1} - P^{III}_{\alpha,2t_i-1}\underline{\alpha} - P^{III}_{x,2t_i-1}\underline{x}_{2t_i-2}}{P^{II}_{2t_i-1}} \\ &= \mu_{1,2t_i-1} + \mu_{\alpha,2t_i-1}\underline{\alpha} + \mu_{x,2t_i-1}\underline{x}_{2t_i-2}. \end{aligned}$$

Period $t : 2t_i - 2 \rightarrow 2$: Given the results from period $2t_i - 1$ for the following periods a recursive relationship for the integrating constant and conditional moments can be established. The kernel $k_t(\underline{\eta}_t)$ is given as

$$k_t(\underline{\eta}_t) = \frac{1}{\sqrt{2\pi}} D_t \exp\left\{ -\frac{1}{2} \left[\underline{\eta}_t' P_t \underline{\eta}_t - 2q_t' \underline{\eta}_t + r_t \right] \right\},$$

where

$$\begin{aligned} P_t &= e_t e_t' + \hat{\alpha}_t \begin{pmatrix} h_t' \\ b_t \end{pmatrix} \begin{pmatrix} h_t & b_t \end{pmatrix} + P^*_t, \\ q_t &= q^*_t + (\hat{\beta}_t - \hat{\alpha}_t a_t) \begin{pmatrix} h_t' \\ b_t' \end{pmatrix}, \\ r_t &= r^*_t - 2\hat{\beta}_t(a_t) + \hat{\alpha}_t(a_t)^2. \end{aligned}$$

The coefficients $\hat{\alpha}_t$ and $\hat{\beta}_t$ are obtained from the auxiliary regressions

$$\log\left[\Phi(\delta_{t+1}\omega_t)\right] = \tilde{c}_o + \tilde{c}_1\omega_t + \tilde{c}_2\omega_t^2,$$

where $\tilde{c}_1 = \hat{\beta}_t$ and $\tilde{c}_2 = -\frac{1}{2}\hat{\alpha}_t$. The corresponding conditional moments are given as

$$\mu_t^c = \frac{q_t^{II} - P_t^{III\prime}\underline{\eta}_{t-1}}{P_t^{II}} \quad \text{and} \quad \sigma_t^c = \frac{1}{\sqrt{P_t^{II}}},$$

where

$$\begin{aligned}
\mu_t^c &= \frac{q_t^{II} - P_t^{III}\underline{\eta}_t}{P_t^{II}} \\
&= \frac{q_{\mu,t}^{II} - P_{\alpha,t}^{III}\underline{\alpha} - P_{x,t}^{III}\underline{x}_t}{P_t^{II}} \\
&= \mu_{1,t} + \mu_{\alpha,t}\underline{\alpha} + \mu_{x,t}\underline{x}_t,
\end{aligned}$$

and the integrating constant takes the form

$$\begin{aligned}
\chi_t(\underline{\eta}_{t-1}) &= \sigma_t^c \Phi\left(\delta_t \omega_{t-1}\right) \\
&\quad \exp\left\{-\frac{1}{2}\left[\underline{\eta}_{t-1}' P_{t-1}^* \underline{\eta}_{t-1} - 2\underline{\eta}_{t-1}{}' q_{t-1}^* + r_{t-1}^*\right]\right\}
\end{aligned}$$

with

$$\begin{aligned}
P_{t-1}^* &= P_t^I - \frac{P_t^{III\prime} P_t^{III}}{P_t^{II}}, \\
q_{t-1}^* &= q_t^I - \frac{q_t^{II} p_t^{III}}{p_t^{II}}, \\
r_{t-1}^* &= r_t - \left(\frac{q_t^{II}}{\sqrt{p_t^{II}}}\right)^2 + \log(p_t^{II}).
\end{aligned}$$

Period 1: For the first period the kernel $k_1(\cdot)$ takes the form

$$k_1(\underline{\eta}_1) = \frac{1}{\sqrt{2\pi}} D_1 \exp\{-\frac{1}{2}[\underline{\eta}_1 P_1 \underline{\eta}_1 - 2q_1\underline{\eta}_1 + r_1]\},$$

where

$$\begin{aligned}
P_1 &= e_1 e_1' + \hat{\alpha}_1 \begin{pmatrix} h_1' \\ b_1 \end{pmatrix} \begin{pmatrix} h_1 & b_1 \end{pmatrix} + P_1^*, \\
q_1 &= q_1^* + (\hat{\beta}_1 - \hat{\alpha}_1 a_1) \begin{pmatrix} h_1' \\ b_1 \end{pmatrix}, \\
r_1 &= r_1^* - 2\hat{\beta}_1(a_1) + \hat{\alpha}_1(a_1)^2.
\end{aligned}$$

$\hat{\alpha}_1$ and $\hat{\beta}_1$ are obtained from the auxiliary regressions ensuring good fit between integrand and importance density

$$\log\left[\Phi(\delta_2\omega_1)\right] = \tilde{c}_o + \tilde{c}_1\omega_1 + \tilde{c}_2\omega_1^2,$$

where $\tilde{c}_1 = \hat{\beta}_1$ and $\tilde{c}_2 = -\frac{1}{2}\hat{\alpha}_1$. Hence, the integrating constant takes the form

$$\chi_1(\underline{\alpha}) = \Phi\left(\delta_1(a_0 - h_0\underline{\alpha})\right) \exp\left\{-\frac{1}{2}\left(\underline{\alpha}' P_0^* \underline{\alpha} - 2\underline{\alpha} q_0^* + r_0^*\right)\right\},$$

where

$$\begin{aligned}
P_0^* &= P_1^I - \frac{P_1^{III\prime} P_1^{III}}{P_1^{II}}, \\
q_0^* &= q_1^I - \frac{q_1^{II} P_1^{III}}{P_1^{II}}, \\
r_0^* &= r_1 - \left(\frac{q_1^{II}}{\sqrt{P_1^{II}}} \right)^2 + \log(P_1^{II}).
\end{aligned}$$

and the conditional moments are given as

$$\mu_1^c = \frac{q_1^{II} - P_1^{II} \underline{\alpha}}{P_1^{II}}, \quad \text{and} \quad \sigma_1^c = \frac{1}{\sqrt{P_1^{II}}}.$$

Sampling of the random coefficients: Since the integrating constant in period 1 is a quadratic form of $\underline{\alpha}$, the kernel is given as

$$k_0(\underline{\alpha}) = \exp\{-\frac{1}{2} \left[\underline{\alpha}' P_0 \underline{\alpha} - 2 q_0 \underline{\alpha} + r_0 \right] \},$$

where

$$\begin{aligned}
P_0 &= \Upsilon + P_0^* + \hat{\alpha}_0 (h_0' h_0), \\
q_0 &= q_0^* + (\hat{\beta}_0 - \hat{\alpha}_o a_0) h_0 + q_\alpha, \\
r_0 &= \hat{\alpha}_0 a_0^2 - 2 \hat{\beta}_0 a_0 + r_0^* + r_\alpha.
\end{aligned}$$

The regression coefficients $\hat{\alpha}_t$ and $\hat{\beta}_t$ are obtained from the auxiliary regressions

$$\log\left[\delta_1 \omega_0\right] = \tilde{c}_o + \tilde{c}_1 \omega_0 + \tilde{c}_2 \omega_0^2,$$

where $\omega_0 = a_0 + h_0 \underline{\alpha}$, $\tilde{c}_1 = \hat{\beta}_t$ and $\tilde{c}_2 = -\frac{1}{2}\hat{\alpha}_t$. Note that via Υ, q_α, and r_α the distributions $f_{gr|\underline{\alpha}}(gr|\underline{\alpha}) f_{\underline{\alpha}}(\underline{\alpha})$ are taken into account. The derivation follows the principles laid down in the Subsection (3.6.1). These parameters are given as

$$\begin{aligned}
\Upsilon &= \Psi + \Omega^{-1}, \\
q_\alpha &= \Psi \hat{\underline{\alpha}}, \\
r_\alpha &= \hat{\underline{\alpha}}' \Psi \hat{\underline{\alpha}} - v_i' \Sigma_{11}^{-1} X^{\text{ran}} (X^{\text{ran}\prime} \Sigma_{11}^{-1} X^{\text{ran}})^{-1} X^{\text{ran}\prime} \Sigma_{11}^{-1} v_i + v_i' \Sigma_{11}^{-1} v_i.
\end{aligned}$$

Thereby

$$\Psi = \begin{pmatrix} X^{\text{ran}\prime} \Sigma_{11}^{-1} X^{\text{ran}} & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \quad \text{and} \quad \hat{\underline{\alpha}} = \begin{pmatrix} (X^{\text{ran}\prime} \Sigma_{11}^{-1} X^{\text{ran}})^{-1} X^{\text{ran}\prime} \Sigma_{11}^{-1} v_i \\ 0 \\ 0 \end{pmatrix},$$

where $v_i = gr_{i\cdot} - \overline{X\beta} - \gamma_1(\cdot) - \gamma_2(\cdot)$. The moments are given as

$$\begin{aligned}
\Sigma_{\underline{\alpha}} &= P_0^{-1}, \\
\mu_{\underline{\alpha}} &= P_0^{-1} q_0,
\end{aligned}$$

and the integrating constant is given as

$$\chi_0 = (2\pi)^{-t_i/2} \exp\{\frac{1}{2}[q_0' P_0 q_0 - r_0]\} \det(P_0^{-1})^{.5} \det(\Omega)^{-.5} \det(\Sigma_{11})^{-.5}$$

Given the EIS regression coefficients the estimate of the integral providing the likelihood contribution is obtained via collecting all integrating constants. It takes therefore the form

$$\hat{p} = \frac{1}{S} \sum_{s=1}^{S} \prod_{t=2}^{2t_i} \left(\frac{D_t^{(s)} \phi(x_t^{(s)}) \chi_t(\underline{x}_{t-1}^{(s)}, \underline{\alpha}^{(s)})}{k_t(\underline{x}_t^{(s)}, \underline{\alpha}^{(s)})} \right) \frac{D_1 \phi(x_1^{(s)}) \chi_1(x_1^{(s)}, \underline{\alpha}^{(s)})}{k_1(x_1^{(s)}, \underline{\alpha}^{(s)})} \frac{f_{\underline{\alpha}}(\underline{\alpha}^{(s)})}{m_0(\underline{\alpha}^{(s)})}.$$

After discarding the terms included in the nominator and denominator, this expression can be restated as

$$\hat{p} = \frac{1}{S} \sum_{s=1}^{S} \left[\prod_{t=2}^{2t_i} \frac{\Phi(\delta_{t+1} \tilde{\omega}_t^{(s)})}{\exp\{-\frac{1}{2}(\tilde{\alpha}_t [\tilde{\omega}_t^{(s)}]^2 - 2\hat{\beta}_t \tilde{\omega}_t^{(s)})\}} \right] \frac{\Phi(\delta_1(a_0 + h_0 \underline{\alpha}^{(s)}))}{\exp\{-.5(\hat{\alpha}_0(a_0 + h_0 \underline{\alpha}^{(s)})^2) - 2\hat{\beta}_0(a_0 + h_0 \underline{\alpha}^{(s)})\}} \chi_0.$$

3.6.3 Monte Carlo Studies for Assessment of Efficient Importance Sampling Accuracy

Three Monte Carlo studies shall be performed to highlight the increase in numerical accuracy achieved by the Efficient Importance Sampler. These experiments are performed for the Bivariate Probit Model with serially correlated errors and random coefficients. This model exhibits the same features for integrational purposes, but is slightly more handy to deal with.

For reference, the results for the Efficient Importance Sampler are compared to the results obtained using the GHK-sampler. Data sets stemming from the bivariate probit model are generated, whereas a constant and two regressor are considered within in both equations. One of the regressors and the constants are assigned to bear a random coefficient. Several parameter constellations are analyzed, with varying degree of serial correlation. The results are based on three different scenarios for the structural parameters $\theta = (\underline{\beta}_1, \underline{\beta}_2, \rho, \psi_1, \psi_2, \underline{\alpha}_1, \underline{\alpha}_2)$. These are

- set *I*: $\underline{\beta}_1 = (-.8, .1, -.3)$, $\underline{\beta}_2 = (.3, -.2, .3)$, $\rho = -.2$, $\psi_1 = -.2$, $\psi_2 = .3$, $\underline{\alpha}_1 = (.4, .5)$, $\underline{\alpha}_2 = (.5, .8)$.
- set *II*: $\underline{\beta}_1 = (-.8, .1, -.3)$, $\underline{\beta}_2 = (.3, -.2, .3)$, $\rho = .2$, $\psi_1 = .8$, $\psi_2 = .3$, $\underline{\alpha}_1 = (.8, .5)$, $\underline{\alpha}_2 = (1, .2)$.
- set *III*: $\underline{\beta}_1 = (-.8, .1, -.3)$, $\underline{\beta}_2 = (.3, -.2, .3)$, $\rho = .6$, $\psi_1 = -.5$, $\psi_2 = .5$, $\underline{\alpha}_1 = (.2, .1)$, $\underline{\alpha}_2 = (.5, .8)$.

Experiment I

The experiment has the following setup. A data set consisting out of one individual and different number of time periods $T = (5, 10, 20, 50)$ is generated. Then the corresponding integral providing the log likelihood is evaluated for 1000 different sets of common random numbers. The integral is evaluated via GHK and GHK-EIS. The results for the simulated (negative) log likelihood are given in Table (3.12) below. Integral evaluation is based in 500 draws. The results indicate a 100fold reduction in the MC standard error across all considered scenarios. The obtained reduction rises as the number of time periods increases, while the observed MC errors are larger, when the underlying serial correlation and correlation across equations is higher. For $T = 5$ the reduction is 5-10fold while for $T = 50$ the reduction is up to 100fold. The differences between the two samplers can be explained on basis of the bias, which the GHK-simulator displays for high dimensional integrals.

The results in Table (3.12) show the reduction in the simulation error, when serial correlation in time and across equations is present. Since the specific contribution of this chapter is the incorporation of heterogeneity within an Efficient Importance Sampler, the experiment is repeated without any consideration of correlation structures, i.e. $\rho = \psi_1 = \psi_2 = 0$. Table (3.13) shows the corresponding results. The reduction in simulation error achieved by the GHK-EIS procedure is heterogeneous. For some scenarios the numerical precision is increased by factor 2 up to factor 5, which is a small reduction compared to results when serial correlation structures have been considered. Note however, that simulation results concerend with the consideration of random coefficients refer to a four dimensional integrational problem compared to the at most 10 dimensional problems when serial correlation is considered. Thus, for the relative low dimensional problem of integration the observed reduction in the simulation error is substantial. Furthermore, one may argue that a two fold reduction in simulation error can be achieved via a fourfold increase of the number of replications employed in the GHK procedure. However, this increase can cause substantial computational burden making the GHK-EIS procedure faster compared to the GHK procedure.

Experiment II

Experiment II checks whether the samplers deliver accurate Hessian matrices in order to have a correct assessment of the sample uncertainty, which is essential for testing, see Geweke et al. (1997). Hence, data sets for the different parameter constellations were generated. Each data set is estimated with the same set of common random numbers and a period length of $T = 20$. Estimation is based on 50 draws for integration. Table (3.14) gives the results for the MC study. The columns report the true parameter value of the data generating process (DGP), the average parameter estimate, the standard deviation of parameter estimates, the root mean squared error, the mean absolute error, and the average standard error calculated via inversion of the Hessian matrix (first for GHK sampler, then for GHK-EIS sampler; from left to right). The results show for all three parameter scenarios that with respect to the mean parameters both samplers deliver average asymptotic standard errors, which are similar to the empirical standard deviations of the estimates. In general deviations between asymptotic and empirical standard deviations are smaller for the GHK-EIS procedure.

For the correlation and variance parameters, the performance of the GHK-EIS procedure is superior compared to the GHK procedure. Mean absolute deviations are smaller for correlation and variance parameters. Also the mean asymptotic standard errors are in general closer to their empirical counterparts for correlation and variance parameters and all three parameter scenarios.

Experiment III

Experiment III checks the transmission of the numerical inaccuracy involved in the integration on parameter estimates for one data set. Therefore a data set under different parameter constellations is generated and repeated estimation is performed using different sets of common random numbers (CRN) for integration. Table (3.15) shows hence for different parameter constellations the true values of the data generating process, the average estimates, and the involved MC errors for the different parameters and the bias. Estimation is based on 50 draws used for each integration. Performance measures are calculated with respect to pseudo true values, which are obtained via estimation based on $S = 500$ draws. The results suggest 10 to 100fold reduction in the numerical standard errors, which indicates a sharp increase in the accuracy of estimation for one data set and the involved testing.

3.6.4 Calculation of Expected Output Losses

The simulation of the involved expectations for cumulated output losses is done in two main steps. Since focus is on average costs for a typical crises scenario, the simulation is not country specific and the country specific random coefficients are numerically integrated out in the intercourse of simulation.

1. Simulate from the marginal distributions of all random coefficients $\{\beta_i, \beta_{1i}, \beta_{2i}\}$ trajectories of size 1000 for each simulation repetition. Also, simulate the errors for the two considered scenarios, i.e. crisis and no crisis scenario, in the following way. For the crisis scenario (currency crisis and/or current account reversal) simulate the errors given that the assumed crisis takes place in period t_0 from the joint distribution of errors, i.e.

$$f(\{e_t,\ {}_1\epsilon_t,\ {}_2\epsilon_t\}_{t=t_0}^{t^*}|\ {}_jy_{t_0} = 1, \tilde{X}), \quad j = \{1, 2\},$$

   where $\tilde{X}$ refers to the constructed regressor profiles capturing a typical crisis environment. The joint distribution is thereby constructed using the decomposition of the joint distribution into the joint conditional distribution of errors after the shock period and the distribution of errors in the shock period t_0 given the occurrence of a crisis. The same is done for the no crisis scenario, i.e. it is simulated from

$$f(\{e_t,\ {}_1\epsilon_t,\ {}_2\epsilon_t\}_{t=t_0}^{t^*}|\ {}_jy_{t_0} = 0, \dot{X}), \quad j = \{1, 2\},$$

   where $\dot{X}$ reflects a typical no crisis environment. Note that this simulation step is done conditionally on the simulated random coefficients, where these enter the joint distribution of errors via the truncation sphere used in the period of shock t_0 to guarantee the occurrence of the particular assumed crisis.

2. Given the errors, iterate over the periods $t = t_0, \ldots, t^*$, in the following way

   (a) Given the simulated trajectories errors, calculate trajectories for ${}_1y_t^*$, ${}_2y_t^*$ and ${}_1y_t$, ${}_2y_t$ correspondingly.

(b) Calculate trajectories for gr_t given ${}_1y_t$, ${}_2y_t$. Proceed with period $t+1$.

Given the trajectories for each period, averages are calculated for each simulation repetition and based on this average the distribution of cumulated crisis costs is approximated via the simulated sample.

3.6.5 Calculation of adjusted R^2

Adjusted coefficients of determination are based on conditional expected random coefficients $\beta_i, \beta_{1i}, \beta_{2i}$ summarized within θ_i, where all available information is used. Denote all other model parameters as $\theta_{/\theta_i}$. Then, the expected random parameters θ_i are calculated via numerical integration as

$$E[\theta_i|\text{data of country } i, \theta] = \frac{\int_{\times(-\infty,\infty)^{k+k_1+k_2}} \theta_i L(\theta, \theta_i; \text{data of country } i) d\theta_i}{\int_{\times(-\infty,\infty)^{k+k_1+k_2}} L(\theta, \theta_i; \text{data of country } i) d\theta_i},$$

where k, k_1, and k_2 denote the dimension of parameters β_i, β_{1i} and β_{2i} respectively. The resulting expected random coefficients are also discussed by Greene (2004b) in the context of the panel probit model. The involved integrational problem is solved using the GHK-EIS procedure. The denominator is readily calculated within the estimation procedure, while the nominator requires a further run of the algorithm. In case of the treatment model the adjusted R^2 is calculated for the growth equation including the expected Mills' ratios for each period, which is only possible, when no serial correlation is considered within the errors (no serial correlation is estimated significantly). Hence the derived adjusted R^2 is only a proxy for model fitness. The considered cases for the Mill's ratio are (for notational details see model description in Subsection 3.3.2)

1. ${}_1y_{it} = 1$, ${}_2y_{it} = 1$:

$$\begin{pmatrix} \frac{\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\rho\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}>h,\ {}_2u_{it}>k)} \\ \frac{\rho\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}>h,\ {}_2u_{it}>k)} \end{pmatrix}.$$

2. ${}_1y_{it} = 0$, ${}_2y_{it} = 1$:

$$\begin{pmatrix} \frac{-\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]-\rho\phi(k)\left[\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}<h,\ {}_2u_{it}>k)} \\ \frac{-\rho\phi(h)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\phi(k)\left[\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}<h,\ {}_2u_{it}>k)} \end{pmatrix}.$$

3. ${}_1y_{it} = 1$, ${}_2y_{it} = 0$:

$$\begin{pmatrix} \frac{\phi(h)\left[\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]-\rho\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}>h,\ {}_2u_{it}<k)} \\ \frac{\rho\phi(h)\left[\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]-\phi(k)\left[1-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr({}_1u_{it}>h,\ {}_2u_{it}<k)} \end{pmatrix}.$$

4. ${}_0y_{it} = 0,\ {}_2y_{it} = 0$:

$$\begin{pmatrix} \frac{\phi(h)\left[-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\rho\phi(k)\left[-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr(\ {}_1u_{it}<h,\ {}_2u_{it}<k)} \\ \frac{\rho\phi(h)\left[-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]+\phi(k)\left[-\Phi\left(\frac{k-\rho h}{\sqrt{1-\rho^2}}\right)\right]}{\Pr(\ {}_1u_{it}<h,\ {}_2u_{it}<k)} \end{pmatrix}.$$

Tab. 3.12: Monte Carlo experiment 1 - Accuracy of efficient importance sampler

	I		*II*		*III*	
	GHK	GHK-EIS	GHK	GHK-EIS	GHK	GHK-EIS
T=5						
MC-Mean	1.4186	1.4191	3.9786	3.9787	3.1516	3.1495
MC-Std	0.0380	0.0034	0.0398	0.0089	0.0638	0.0045
MC-coeff. of var.	0.0268	0.0024	0.0100	0.0022	0.0203	0.0014
T=10						
MC-Mean	15.1189	15.0735	5.3296	5.3221	3.8515	3.8486
MC-Std	0.2916	0.0036	0.1642	0.0128	0.0903	0.0085
MC-coeff. of var.	0.0193	0.0002	0.0308	0.0024	0.0235	0.0022
T=20						
MC-Mean	15.2034	15.2006	7.9509	7.8700	14.4205	14.3873
MC-Std	0.1100	0.0035	0.3676	0.0173	0.2780	0.0105
MC-coeff. of var.	0.0072	0.0002	0.0462	0.0022	0.0193	0.0007
T=50						
MC-Mean	30.4523	30.4057	44.2886	42.8124	38.9467	37.7662
MC-Std	0.2973	0.0058	1.3572	0.0249	1.3117	0.0128
MC-coeff. of var.	0.0098	0.0002	0.0306	0.0006	0.0337	0.0003

Note: MC-estimation of log-likelihood contribution for simulated data using the different parameter sets *I*-*III*. The mean standard deviation and the coefficient of variation are obtained from 1000 independent replications of the MC estimation. The estimates are based upon a simulation sample size of $S = 500$.

Tab. 3.13: Monte Carlo experiment 1 - Accuracy of efficient importance sampler (only heterogeneity)

	I		*II*		*III*	
	GHK	GHK-EIS	GHK	GHK-EIS	GHK	GHK-EIS
T=5						
MC-Mean	8.0949	8.0516	7.3368	7.3069	9.8493	9.1322
MC-Std	0.3669	0.3207	0.3593	0.2758	1.3965	0.2971
MC-coeff. of var.	0.0453	0.0398	0.0490	0.0377	0.1418	0.0325
T=10						
MC-Mean	7.0762	6.9761	6.6131	6.5089	7.7376	7.5489
MC-Std	0.5514	0.2034	0.6080	0.3191	0.6986	0.1429
MC-coeff. of var.	0.0779	0.0292	0.0919	0.0490	0.0903	0.0189
T=20						
MC-Mean	26.6542	25.1952	25.3093	25.0042	24.6037	24.2676
MC-Std	2.3258	0.3155	1.2212	0.7678	1.1086	0.5466
MC-coeff. of var.	0.0873	0.0125	0.0483	0.0307	0.0451	0.0225
T=50						
MC-Mean	69.4530	67.4947	54.2088	53.1315	24.6484	21.4649
MC-Std	2.8107	0.8357	1.8595	0.8776	2.5173	0.5987
MC-coeff. of var.	0.0405	0.0124	0.0343	0.0165	0.1021	0.0279

Note: MC-estimation of log-likelihood contribution for simulated data using the different parameter sets *I*-*III*. The mean standard deviation and the coefficient of variation are obtained from 1000 independent replications of the MC estimation. The estimates are based upon a simulation sample size of $S = 500$.

Tab. 3.14: Monte Carlo experiment 2 - Accuracy of efficient importance sampler

DGP		GHK					GHK-EIS				
T=20		$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$	$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$
β_{11}	-0.8	-0.7869	0.1559	0.1226	0.1525	0.3347	-0.8438	0.1489	0.1294	0.1516	0.1541
β_{12}	0.1	0.1368	0.1543	0.1336	0.1548	0.2290	0.1318	0.1612	0.1340	0.1603	0.1681
β_{13}	-0.3	-0.2793	0.2134	0.1659	0.2091	0.2366	-0.2885	0.1836	0.1420	0.1793	0.2037
β_{21}	0.3	0.2542	0.2307	0.2001	0.2294	0.2579	0.2724	0.2208	0.1648	0.2169	0.1660
β_{22}	-0.2	-0.1122	0.1698	0.1372	0.1873	0.1891	-0.128	0.1830	0.1454	0.1924	0.1625
β_{23}	0.3	0.3588	0.2151	0.1892	0.2178	0.2409	0.3609	0.2387	0.1983	0.2405	0.2007
ρ	-0.2	-0.1241	0.0813	0.0841	0.1097	0.0753	-0.1854	0.0798	0.0659	0.0792	0.0694
ψ_1	-0.2	-0.1736	0.0726	0.0598	0.0755	0.0965	-0.2246	0.0856	0.0733	0.0870	0.0667
ψ_2	0.3	0.2430	0.0766	0.0824	0.0939	0.0727	0.2680	0.0731	0.0648	0.0781	0.0655
σ_{11}	0.4	0.6194	0.1972	0.2690	0.2917	0.4125	0.6111	0.1317	0.2260	0.247	0.1104
σ_{12}	0.5	0.4923	0.4549	0.4163	0.4435	0.6731	0.6669	0.2943	0.2810	0.3318	0.2559
σ_{21}	0.5	0.8026	0.2115	0.3116	0.3661	0.1965	0.7488	0.1340	0.2488	0.2810	0.1223
σ_{22}	0.8	0.6284	0.5158	0.4302	0.5313	0.8472	0.7621	0.2216	0.1694	0.2193	0.2573
T=20		$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$	$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$
β_{11}	-0.8	-0.8211	0.2313	0.1732	0.2264	0.2613	-0.8761	0.2356	0.1710	0.2419	0.2440
β_{12}	0.1	0.1046	0.1345	0.1066	0.1311	0.1981	0.1210	0.1499	0.1216	0.1476	0.1866
β_{13}	-0.3	-0.3237	0.2012	0.1652	0.1975	0.2100	-0.3152	0.2208	0.1900	0.2158	0.2185
β_{21}	0.3	0.2602	0.2665	0.2226	0.2628	0.2385	0.3206	0.2014	0.1585	0.1974	0.2031
β_{22}	-0.2	-0.1442	0.1230	0.1021	0.1323	0.1785	-0.1437	0.1235	0.1001	0.1328	0.1695
β_{23}	0.3	0.4139	0.199	0.1746	0.2249	0.1890	0.4075	0.1865	0.1688	0.2112	0.1808
ρ	0.2	0.1371	0.0474	0.0630	0.0780	0.0728	0.2138	0.0526	0.0422	0.0531	0.0806
ψ_1	0.8	0.7511	0.0956	0.0846	0.1053	0.0604	0.7672	0.0601	0.0575	0.0671	0.0474
ψ_2	0.3	0.2627	0.0552	0.0585	0.0655	0.0699	0.2841	0.0647	0.0539	0.0650	0.0668
σ_{11}	0.8	0.6094	0.4645	0.4020	0.4912	0.4795	0.8832	0.3114	0.2576	0.3147	0.3393
σ_{12}	0.5	0.2041	0.2340	0.3289	0.3736	0.7750	0.5611	0.3625	0.3127	0.3586	0.4533
σ_{21}	1	1.0899	0.2540	0.1933	0.2634	0.2148	1.0368	0.1963	0.1608	0.1949	0.1453
σ_{22}	0.2	0.3309	0.2768	0.2443	0.2998	0.4701	0.2971	0.2772	0.2486	0.2871	0.593
T=20		$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$	$\bar{\hat{\theta}}$	sd	RMSE	MAE	$\overline{ASD}$
β_{11}	-0.8	-0.7811	0.1012	0.0750	0.1004	0.1378	-0.8442	0.1227	0.0974	0.1275	0.1377
β_{12}	0.1	0.1130	0.1325	0.1010	0.1298	0.1675	0.1239	0.1375	0.1080	0.1361	0.1635
β_{13}	-0.3	-0.2828	0.1552	0.1194	0.1522	0.1844	-0.3046	0.1686	0.1269	0.1644	0.1739
β_{21}	0.3	0.2693	0.2593	0.1846	0.2546	0.1666	0.3041	0.1897	0.1293	0.1850	0.1686
β_{22}	-0.2	-0.1279	0.1710	0.1520	0.1816	0.1690	-0.1597	0.1829	0.1553	0.1828	0.1606
β_{23}	0.3	0.3534	0.2381	0.1900	0.2382	0.1967	0.3400	0.2175	0.1815	0.2158	0.2067
ρ	0.6	0.4378	0.0567	0.1622	0.1714	0.0582	0.5953	0.0727	0.0543	0.0710	0.0623
ψ_1	-0.5	-0.4369	0.0544	0.0705	0.0824	0.0556	-0.51	0.0568	0.0452	0.0562	0.0457
ψ_2	0.5	0.4633	0.0546	0.0541	0.0647	0.0617	0.4918	0.0422	0.0317	0.0420	0.0534
σ_{11}	0.2	0.3856	0.1158	0.1897	0.2172	0.0861	0.4315	0.1005	0.2333	0.2513	0.0807
σ_{12}	0.1	0.2978	0.2693	0.2568	0.3287	0.2978	0.2909	0.2386	0.2293	0.3009	0.2627
σ_{21}	0.5	0.7103	0.2107	0.2570	0.2939	0.1298	0.7217	0.1407	0.2218	0.2606	0.1408
σ_{22}	0.8	0.7096	0.5119	0.3932	0.5071	0.3974	0.8114	0.2765	0.2093	0.2697	0.2544

Note: Estimation of parameters for simulated data using the different parameter sets *I-III*.

Tab. 3.15: Monte Carlo experiment 3 - Accuracy of efficient importance sampler

pseudo true values		GHK			GHK-EIS		
T=20		$\bar{\hat{\theta}}$	sd	bias	$\bar{\hat{\theta}}$	sd	bias
β_{11}	-0.6539	-0.6661	0.0786	0.0624	-0.6528	0.0006	0.0011
β_{12}	0.1365	0.1330	0.0210	0.0174	0.1364	0.0003	0.0002
β_{13}	-0.1850	-0.2155	0.0757	0.0671	-0.1843	0.0014	0.0011
β_{21}	0.2257	0.2559	0.1236	0.1023	0.2252	0.0004	0.0005
β_{22}	-0.0561	-0.0588	0.0203	0.0160	-0.0564	0.0002	0.0003
β_{23}	0.2463	0.2318	0.0792	0.0604	0.2457	0.0006	0.0008
ρ	-0.2202	-0.1739	0.0361	0.0481	-0.2195	0.0006	0.0007
ψ_1	-0.1268	-0.1057	0.0248	0.0266	-0.1251	0.0008	0.0017
ψ_2	0.2459	0.2272	0.0260	0.0275	0.2471	0.0010	0.0014
σ_{11}	0.6198	0.6534	0.1105	0.0872	0.6149	0.0023	0.0049
σ_{12}	0.6650	0.5008	0.3682	0.3377	0.6580	0.0107	0.0102
σ_{21}	0.8702	0.8850	0.1257	0.0992	0.8678	0.0017	0.0026
σ_{22}	0.7464	0.5343	0.4896	0.4471	0.7334	0.0069	0.0131
T=20		$\bar{\hat{\theta}}$	sd	bias	$\bar{\hat{\theta}}$	sd	bias
β_{11}	-0.7715	-0.6756	0.0788	0.0960	-0.7703	0.0012	0.0014
β_{12}	0.2733	0.2633	0.0224	0.0201	0.2733	0.0010	0.0009
β_{13}	-0.1599	-0.1556	0.0578	0.0442	-0.1593	0.0012	0.0012
β_{21}	0.0163	0.1145	0.1083	0.1155	0.0168	0.0007	0.0007
β_{22}	-0.2389	-0.2358	0.0292	0.0201	-0.2391	0.0003	0.0003
β_{23}	0.4499	0.4441	0.0906	0.0673	0.4495	0.0013	0.0011
ρ	0.1671	0.1157	0.0393	0.0547	0.1657	0.0011	0.0016
ψ_1	0.7559	0.7121	0.0565	0.0574	0.7533	0.0015	0.0027
ψ_2	0.3121	0.2925	0.0332	0.0316	0.3123	0.0010	0.0008
σ_{11}	0.7318	0.5426	0.3717	0.3183	0.7349	0.0057	0.0049
σ_{12}	0.816	0.3078	0.3386	0.5183	0.808	0.0068	0.0091
σ_{21}	1.1484	1.1252	0.1260	0.0967	1.1406	0.0045	0.0079
σ_{22}	0.4806	0.4057	0.3871	0.3517	0.4743	0.0114	0.0095
T=20		$\bar{\hat{\theta}}$	sd	bias	$\bar{\hat{\theta}}$	sd	bias
β_{11}	-0.8985	-0.8285	0.0589	0.0795	-0.8942	0.0013	0.0043
β_{12}	0.1964	0.1448	0.0313	0.0516	0.1941	0.0010	0.0023
β_{13}	-0.294	-0.3123	0.0425	0.0385	-0.2931	0.0013	0.0013
β_{21}	0.2307	0.2242	0.0766	0.0605	0.2304	0.0007	0.0006
β_{22}	-0.0837	-0.0794	0.0414	0.0307	-0.0836	0.0008	0.0006
β_{23}	0.2195	0.1901	0.0928	0.0661	0.21854	0.0011	0.0013
ρ	0.5806	0.4172	0.0295	0.1634	0.5740	0.0032	0.0066
ψ_1	-0.4678	-0.3813	0.0241	0.0865	-0.4636	0.0011	0.0041
ψ_2	0.5144	0.4803	0.0409	0.0464	0.5131	0.0017	0.0016
σ_{11}	0.4283	0.4524	0.0897	0.0765	0.4161	0.0032	0.0122
σ_{12}	0.6017	0.3426	0.2753	0.3147	0.5934	0.0047	0.0101
σ_{21}	0.7400	0.7477	0.1624	0.1323	0.7389	0.0020	0.0019
σ_{22}	0.9393	0.6277	0.3754	0.3574	0.9288	0.0060	0.0105

Note: Estimation of parameters for simulated data using the different parameter sets *I-III*.

4. CHARACTERIZATION OF CURRENT ACCOUNT REVERSALS VIA MARKOV-SWITCHING MODELS

4.1 Introduction

The experience that changes in world capital flows can cause costly adjustment processes has triggered several empirical studies analyzing determinants and resulting economic costs of these crises, see among others Milesi-Ferretti and Razin (1998) and Edwards (2004). Reverting current account balances are perceived as a readjustment of unsustainable current account deficits. The intertemporal approach to current account imbalances provides a consistent theoretical framework to analyze the sustainability of current account deficits, see Cashin and McDermott (1996). An empirical analysis of current account sustainability is provided by Ansari (2004) on a country level. Sustainability of the current account balance is related to the analysis of abrupt changes in the current account balance, as it is analyzed in what way imbalances are likely to end up in a large downswing of economic growth. An abrupt change or reversal is defined in two ways. Firstly and more prominent in the literature, a reversal is defined as a percentage reduction in average current account deficit relative to gross domestic product (GDP) exceeding a certain threshold say 3%, see e.g. Alesina and Perotti (1997). This approach has been adapted in the previous chapters. Secondly, as proposed by Baltagi and Manzocchi (1999), a current account reversal can be backtraced to changes in the dynamic behavior of the current account. Therefore, the timing of reversals is provided by structural break tests, which account for dynamic characteristics of the data. While the first definition can be easily implemented, the usage of moving averages possibly leads to an inconsistent timing of the reversals, when volatile cycles are present. While this deficiency is overcome by the second methodology, it relies on relatively long data series to meet the testing prerequisites and analysis of the determinants of current account is only provided in a two step approach based on the results of the structural break tests. Another important feature is country specific heterogeneity, which is not addressed by this methodology for identification of reversals.

This chapter therefore proposes an alternative way to decide on the occurrence and determinants of reversals in terms of a regime switching model. Based upon the approaches for speculative attacks set up by Martinez-Peria (2002), a Markov Switching model is used for identification of reversals and their determinants.[1] Using Markov Switching models allows, in contrast to ad hoc criteria where only short time intervals of current account balance are con-

[1] Another application of regime switching models in the field of current account is the assessment of leading indicators, which are used to predict current account reversals. Using a Markov Switching dynamic factor model, Chauvet and Dong (2004) assess the proximity of factor states and the Asian currency crises in 1998. This study underlines the seemingly non linear behavior of current account.

sidered for reversal definition, to use all sample information for characterization of the reversal episodes. Regime switching models are frequently used for timing purposes in the context of business cycle turning points, see Chauvet (1998). Regime switching models allow to construct a binary variable indicating the occurrence of a reversal, what allows to compare the reversal episodes identified under regime switching with those delivered by ad hoc criteria. In contrast to the methodology of Martinez-Peria (2002), this chapter considers no pooling of data across countries, but incorporates latent county specific heterogeneity. The latent country specific heterogeneity is modeled via specification of the mean equation, while the parameters ruling the state probabilities are obtained via pooling information across countries. As noted by Frühwirth-Schnatter and Kaufmann (2008) neglect of latent country specific heterogeneity would induce a bias if the data generating mechanism differs substantially between countries.

In order to assess, whether a characterization of current account reversals as regime shifts yields insight into the relationship of current account and economic growth performance, a vector autoregressive Markov Switching (MS-VAR) model is estimated to assess the relationship between growth and current account dynamics. The model allows for two states of each dependent variable, while transition between these two states are ruled by a single Markov process. The model can be linked to the intertemporal approach to current account, where current account is used in a small economy setup for consumption smoothing, see Gosh and Ostry (1995) and Kano (2003) for an economic treatment of this issue. Via modeling different regimes, the model allows for shifts in the relation of economic growth and current account. The identified differences between the two states of economic growth allow to obtain a measure for reversal costs. Furthermore as mean equations are country specific, the model delivers a country specific state difference, which provides insight into the distribution of reversal costs among countries.

The results of the analysis point out differences with respect to the timing of reversals. Reversals identified under regime switching are timed up to two periods earlier or later than reversals suggested by ad hoc criteria. These differences in timing however do not alter the results documented in the literature concerning the determinants of reversals, as the same set of macroeconomic variables is found to have significant influence. The estimated costs of reversals also correspond to the estimates given in the literature and amount to a reduction of 4% of annual GDP growth.

The chapter proceeds as follows. Within Section 4.2, the data set for comparison of ad hoc crises with crises episodes identified under the regime switching approach in Chapter 4 is shortly summarized. Section 4.3 provides also an overview of reversal episodes identified by ad hoc criteria and discusses potential problems arising from the use of ad hoc criteria. Section 4.4 presents the Markov switching models used in this analysis and the estimation procedures. Section 4.5 states the empirical findings and Section 4.6 concludes.

4.2 Data Description and Problems of Reversal Identification via ad hoc Criteria

The data set used to analyze the identification of reversals in Chapter 4 focuses mainly on the time series of current account balance relative to GDP. These time series are taken from the

World Development Indicators database (2005). The considered time series are available for 96 countries over the period 1970-2004.[2] Note that focusing on these time series allows to analyze a larger data set than in the previous chapters. However, when state probabilities are linked to explaining variables, which are available only for a subsample, the data sets shrinks to 67 of the considered countries. The list of variables considered for modeling time varying state probabilities is a subset of the set of variables considered in Chapter 2 and Chapter 3 in order to allow a sufficiently larg time dimension of the considered panel data set. Table (4.1) gives an overview of these variables. Not all variables employed in the previous chapters are investigated, since some would limit the available time range for some countries substantially.

A bundle of ad hoc criteria focusing on certain time series properties of current account balance delivers an identification scheme, which allows to classify time periods as reversals. Identification of reversals is therefore not data driven as proposed by Bagnai and Manzocchi (1999). To attenuate the effect of ad hoc criteria on empirical results, most studies check the results for sensitivity against different ad hoc identification schemes. In the following different identification schemes are summarized, which are discussed in the literature by Milesi-Ferretti and Razin (1998), Frankel and Rose (1996), and Edwards (2004), six in total.[3] Reversals are characterized as changes in the average level of current account balance. According to scheme $(I.a)$ a reversal episode in period t is given when the current account balance in t is indeed a deficit and the average current account deficit in the periods t to $t+2$ compared to the average current balance over periods $t-3$ to $t-1$ is reduced by at least 3%. A further restriction is that for a positive reversal the deficit level after the reversal does not exceed 10%. In order to avoid that the same reductions show up twice in the averages, scheme $(I.b)$ allows no further reversal in the consecutive two years of a reversal. Scheme $(I.c)$ restricts the dynamics in the aftermath of a reversal. The maximum deficit after a reversal is not allowed to exceed the minimum deficit before the reversal in order to classify the period as a reversal. Scheme (II) and its forms a, b and c differ from scheme (I) only with respect to the shift magnitude of average current account reduction triggering a reversal, which has to exceed 5% now.[4]

The number of reversals identified under the alternative identification schemes are reported in Table (4.2). Entries on the main diagonals provide the number of identified reversals for the alternative schemes, whereas the other entries provide the number of reversals which are

[2] These countries are: Albania, Algeria, Angola, Argentina, Bangladesh, Belize, Benin, Bhutan, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo. Rep., Costa Rica, Cote d'Ivoire, Dominica, Dominican Republic, Ecuador, Egypt. Arab Rep., El Salvador, Ethiopia, Fiji, Gabon, Gambia. The, Ghana, Grenada, Guatemala, Guinea, Haiti, Honduras, Hungary, India, Indonesia, Jamaica, Jordan, Kenya, Lao PDR, Lebanon, Lesotho, Madagascar, Malawi, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Nepal, Nicaragua, Niger, Nigeria, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Romania, Rwanda, Samoa, Senegal, Seychelles, Sierra Leone, Solomon Islands, South Africa, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Swaziland, Syrian Arab Republic, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Uganda, Uruguay, Vanuatu, Venezuela. RB,Zimbabwe.

[3] These studies draw on a definition of abrupt changes given by Alesina and Perrotti (1997) in the context of fiscal crises. Furthermore, two more scenarios than in Chapter 2 are analyzed to illustrate the necessity to restrict current account dynamics for reversal identification.

[4] Note that schemes $I.b$, $I.c$, $II.b$, and $II.c$ correspond to schemes II, I, IV, III of Chapter 2.

jointly identified by alternative schemes. In total data summarizes 2240 time periods, since three year averages are considered. When all identification schemes are applied simultaneously only 34 reversals are identified from a maximum number of 437 reversals under scheme $I.a$. The restriction of the consecutive two periods leads to a reduction of identified reversals from 437 ($I.a$) to 206/222 ($I.b/I.c$). Hence the same reduction seems to show up approximately twice.

The problems associated with the identification of current account reversals via ad hoc criteria are illustrated in Figure (4.1). The case of Swaziland (upper left) demonstrates that a restriction of the dynamics within the periods after a reversal may not be sufficient to guaranty that the same upward movements of the current account balance shows up twice. Furthermore it can be noticed for the selected countries that the reversal identified by schemes relying on a three percent reduction (o-lines) occur up to two periods earlier than reversals, which rely on a five percent reduction of current account (+-lines). This can also been seen in Table (4.2), where not all reversals identified under regime $II.c$ are re-identified under scheme $I.c$. Problems with a unique timing of a reversal, which may be hindering for explaining these events, are also present in the case of Bhutan (upper right panel of Figure (4.1)). The lower left panel of Figure (4.1) shows the identified reversals for Venezuela. The case of Venezuela gives the impression of overall volatile behavior of current account balance, which is not untypical for oil exporting countries. The high volatility, characterized by large up and downswings, may lead to a classification of periods as reversals, despite the fact that these reductions lack the criteria of a sustainable reduction of current account as it is not sustained over a longer period.

This selected country evidence shall underline the argument that ad hoc criteria inherit some difficulties with respect to a unique timing of reversal episodes and have also difficulties in distinguishing large volatility of current account balances from sustained deficit reductions. Therefore the next section presents an empirical model in terms of a regime switching approach dealing with these two issues. The framework is extended to allow also an analysis of factors influencing the probability of a reversal and provide an alternative way to assess the reduction of growth caused by the occurrence of crises.

4.3 Model Description

Several types of Markov Switching models shall be used to identify current account reversals. In particular a two state Markov Switching model is used to identify reversals, which are in general characterized as a sharp and persistent reduction in current account deficits. The first regime of the Markov switching model is therefore labeled as the unsustainable state of current account, while the second state characterizes the current account after the reversal, when adjustment to a more sustainable level of current account balance has taken place. The Markov Switching models presented here allow for country specific mean and volatility of the current account relative to GDP.[5] Two different forms of mean switching behavior and constant as well as time varying transition probabilities shall be analyzed. The model for current account balance relative to

[5] Frühwirth-Schnatter and Kaufmann (2008) consider an alternative form to incorporate heterogeneity into a panel of time series subject to regime shifts based on clustering.

GDP of country i at time t is given as

$$ca_{it} = \mu_{iS_{it}} + \sum_{l=1}^{L} \rho_{il} ca_{it-l} + e_{it}, \qquad e_{it} \sim \mathcal{N}(0, \sigma_i^2), \tag{4.1}$$

or as

$$ca_{it} = \mu_{iS_{it}} + \sum_{l=1}^{L} \rho_{il}(ca_{it-l} - \mu_{iS_{it}}) + e_{it}, \qquad e_{it} \sim \mathcal{N}(0, \sigma_i^2), \tag{4.2}$$

where

$$\mu_{iS_{it}} = \begin{cases} \mu_{i0}, & \text{if } S_{it} = 0; \\ \mu_{i1}, & \text{if } S_{it} = 1, \end{cases} \tag{4.3}$$

where the condition $\mu_{i0} < \mu_{i1}$ is induced to hinder label switching. Equation (4.1) describes the current account as an autoregressive process with a regime dependent constant. It allows only the intercept to be subject to regime switching (MSI) implying a more gradual transition between the two regimes. In contrast, within Equation (4.2), the complete mean is subject to regime shifts thus allowing for a more abrupt transition between the two states (MSM).

In both characterizations, the parameters ruling the current account dynamics are country specific, as well as the error variance. Heterogeneity within the model parameters is approached via a fixed and a random coefficients setup. The parameters are either country specific and fix or modeled as random variables from a common distribution, where the following distributional assumptions are implemented

$$\mu_{i0} \overset{\text{iid}}{\sim} \mathcal{N}(\mu_0, \sigma_0), \quad \mu_{i1} \overset{\text{iid}}{\sim} \mathcal{TN}_{(\mu_{i0},\infty)}(\mu_1, \sigma_1), \quad \sigma_i \overset{\text{iid}}{\sim} \mathcal{LN}(\mu_\sigma, \sigma_\sigma).$$

The truncation for μ_{2i} is introduced to hinder the problem of label switching of states discussed in the literature on Markov Switching models, see Frühwirth-Schnatter (2006).[6] The fixed coefficient approach allows to deal with a very flexible form of the country specific heterogeneity, but causes a high parametrization, which hinders to evaluate the parameters uncertainty by means of the Hessian. This deficiency is overcome by random coefficients approach providing a parsimonious yet flexible handling of the heterogeneity.[7]

Furthermore, the Markov process ruling the regime switches is also country specific, although the parameters within the state probabilities given as

$$P(S_{it+1} = 0 | S_{it} = 0) = F(X_{it}\beta_0), \tag{4.4}$$

$$P(S_{it+1} = 1 | S_{it} = 1) = F(X_{it}\beta_1), \tag{4.5}$$

are estimated via pooling the information available in the panel data set. The functional form of $F(\cdot)$ is a logit type probability given as

$$F(X_{it}\beta_j) = \frac{\exp\{X_{it}\beta_j\}}{1 + \exp\{X_{it}\beta_j\}}, \quad j = \{0, 1\}.$$

[6] As an alternative to the Log-Normal distribution for the conditional variance parameter, also a truncated normal distribution has been considered yielding similar results.

[7] The number of parameters is reduced from 384 country specific parameters in the preferred fixed coefficient specification to 8 in the corresponding random coefficients.

If the regressors X_{it} ruling the state probabilities only include a constant, the classical specification of Hamilton (1989,1990) is given in a reparameterized form. Consideration of these time varying transition probabilities allows to assess whether variables analyzed in the empirical literature as determinants of current account reversals function also as indicator of regime switching interpreted as current account reversals. The regime switching approach as considered here provides hence a simultaneous analysis of the timing and determinants of current account reversals.

Estimation is performed in case of the fixed coefficient setup using the EM-algorithm based on the smoothing algorithm of Kim (1994). For the random effects model Simulated Maximum Likelihood estimation is performed based on the filtering approach of Hamilton (1989,1990). The details on estimation are provided within Section 4.6 of this chapter for both model specifications. Estimation of time varying state probabilities in the context of the EM-algorithm is discussed by Diebold et al. (1994). They propose a linearization of the optimization problem involved in estimation of the parameters in the state probabilities. Extension of this linearization scheme towards the panel context provides inaccurate results stemming from the linearization scheme. Hence, time varying state probabilities are only considered in the context of the random coefficients approach via Simulated Maximum Likelihood estimation.

Testing the hypothesis of switching mean behavior is difficult as classical testing preliminaries are not fulfilled, e.g. under the null hypothesis of no switching the state probabilities of the Markov process are not identified.[8] The information criteria of Akaike (AIC) and Schwarz (BIC) are hence used to assess the adequacy of regime switching models for the current account.

The analysis proceeds by assessing the relationship between current account and economic growth. Given the framework of a small open economy, this relationship arises from utility maximizing behavior of a representative household who uses the current account to temporarily smooth income shocks hitting the economy. As it is documented in the literature, non-linearities that are caused by sharp current account movements are observed within this relationship, therefore indicating the presence of sharp and in terms of economic growth costly adjustment processes, see e.g. Edwards (2004) and the analysis in the previous chapters. In the following, a Markov Switching vector autoregressive model (MS-VAR) is proposed to asses the costs of reversals. The model is used as it possibly overcomes the deficiency of former approaches, which do not account for heterogeneity of the sample constituents and rely on ad hoc criteria for reversal identification. The proposed model is given as

$$\begin{pmatrix} gr_{it} \\ ca_{it} \end{pmatrix} = \begin{pmatrix} \mu_{1iS_{it}} \\ \mu_{2iS_{it}} \end{pmatrix} + \sum_{l=1}^{L} \Phi_{il} \begin{pmatrix} gr_{it-l} \\ ca_{it-l} \end{pmatrix} + \begin{pmatrix} e_{1it} \\ e_{2it} \end{pmatrix}, \tag{4.6}$$

[8] Formal tests dealing with the problem of nuisance parameters have been developed by Hansen (1992) and Garcia (1998). The Hansen test is computationally burdensome and it is difficult to get access to the distribution of the LR test statistic as the panel character makes simulation of the process trifling. Garcia's test builds upon the results of Davies (1987). However, according to Andrews and Ploberger (1994) the sufficient conditions linked to the non-singularity of the matrix of second derivatives under the null are not satisfied.

with

$$\begin{pmatrix} e_{1it} \\ e_{2it} \end{pmatrix} \sim \mathcal{N}(0, \Sigma_i), \tag{4.7}$$

where both equations are allowed to possess country specific dynamics and the correlation between both equations is comprised within the matrix Σ_i. Again state dependence is assumed to govern the intercepts only, i.e.

$$\mu_{1iS_{it}} = \begin{cases} \mu_{1i0}, & \text{if } S_{it} = 0; \\ \mu_{1i1}, & \text{if } S_{it} = 1, \end{cases} \qquad \mu_{2iS_{it}} = \begin{cases} \mu_{2i0}, & \text{if } S_{it} = 0; \\ \mu_{2i1}, & \text{if } S_{it} = 1, \end{cases} \tag{4.8}$$

where $\mu_{1i0} > \mu_{1i1}$ and $\mu_{2i0} < \mu_{2i1}$. The latent state variable can therefore be interpreted as representing the economic state of the country influencing economic growth and the relative current account deficit. Thereby, state $S_{it} = 0$ is labeled as an economic environment with an unsustainable current account deficit and potentially higher growth, whereas $S_{it} = 1$ reflects an economic environment with a more sustainable current account deficit and potentially lower growth. The differences between the regime constants can serve as an approximate measure for costs of reversals, as it provides information about the regime differences. In the context of the MS-VAR model only the fixed coefficient specification is considered. Consequently, the analysis is only performed with constant state probabilities, since parameter uncertainty via means of the Hessian is not accessible. A full random coefficients approach would increase the dimension of integration to a level, where special measures via improved sampling schemes are required to guard against numerical inaccuracy, which is left for future research. The estimation is hence done with the EM-algorithm as a stable estimation procedure, where details are provided in Section 4.6. Within the considered models reversals can be identified via estimated state probabilities.[9] A reversal is identified, when the probability that in period $t-1$ the less sustainable state prevails exceeds 50% while in period t the probability of the more sustainable state is larger than 50%. In short

$$P(S_{it-1} = 0|I) \geq 0.5 \quad \text{and} \quad P(S_{it} = 1|I) \geq 0.5. \tag{4.9}$$

Thereby I denotes the information set available at time t. As for reversal identification the state probabilities shall reflect all sample information available, they are given as smoothed probabilities, which are delivered by the Kim smoother incorporated within the EM-algorithm and appended to Simulated Maximum Likelihood estimation, see Section 4.6. The identified reversal episodes are compared to the episodes delivered by ad hoc criteria. This comparison is performed via analysis of the reversal episodes jointly identified by the different approaches.

4.4 Empirical Results

The estimation results will be discussed in two parts. The first part is concerned with the comparison of reversal episodes identified by ad hoc criteria and those identified by the regime

[9] Note that the two regimes considered for description of unsustainable and more sustainable states of the current account balance relative to GDP possibly identify only extreme values the relative current account balance and hence identify no sustained current account deficit reduction. However, the same caveat applies to the use of ad hoc criteria for reversal identification.

switching approaches. Also a set of factors explaining reversals considered in the literature, see e.g. Frankel and Rose (1996) and the previous chapters, is reviewed within this framework. The second presents the estimation results of the Markov-Switching VAR model and gives an approximate measure of reversal costs.

4.4.1 Identification and Determinants of Reversals

As a first step to investigate the adequacy of regime switching models for identification of reversal episodes, the performance of simple linear autoregressive models is compared to the performance of the Markov Switching models. Comparison of model specifications is based on likelihood values and information criteria (AIC and BIC), given the fact that the models are not nested. Table (4.3) gives the results for the fixed coefficient specification. The first row gives the mean over all countries of the constant in case of the linear models, otherwise the constant in the first regime is given, which can be characterized as the less sustainable. When the current account ratio is regressed only on a constant the average deficit amounts to -5.07% of GDP. The associated average conditional variance shows a considerable degree of variation for the mean deficit among countries. The fifth row provides the average variation over time of all countries indicating that large fluctuations of current account can be observed. Again the associated standard deviation across countries suggests a considerable degree of heterogeneity among countries, i.e. some countries show a more stable pattern of current account than others. Including country specific dynamics via an autoregressive specification leads to an improvement of the likelihood value from -6619.9 to -6158.5 suggesting that the current account dynamics is persistent to some degree. The mean of the estimated autoregressive parameters (row 7) is 0.4834. The dynamic behavior varies largely between countries, which is indicated by the standard deviation given as 0.2357.[10] In addition, the specified AR(2) model seems not to capture further aspects of dynamics as it is not preferred to the more parsimonious AR(1) specification. Summarizing, the results of the linear models suggest the presence of latent country specific heterogeneity influencing the data generating process.

The performance of the simplest Markov Switching model without autoregressive dynamics shows a dilemma, which is brought about by the analysis of current account reversals. The log likelihood value only exceeds the simplest linear model with a constant. This may be due to the fact that reversals are indeed rare events causing an over parametrization of the model, as some countries do not experience a reversal. Nevertheless the additional regime allows to discriminate between an unsustainable level of current account and a more sustainable level. The corresponding level of the unsustainable regime is -9.31 % of GDP, whereas the more sustainable level corresponds to a current account surplus of 0.09 % of GDP. The two corresponding standard deviations suggest that both regimes overlap, i.e. for some countries the unsustainable current account state has a level, which would be characterized as sustainable for another country. This heterogeneity is consistent with the hypothesis of 'stages of development' put forward by Fischer and Frenkel (1974) suggesting that countries moving from a low to an intermediate stage

[10] Note that no value of the autoregressive parameter exceeds 0.88 indicating stationarity for all panel members.

of economic development start to import capital resulting in current account deficits. Thus the notion of sustainability seems to depend on the degree of economic development a country has reached. Incorporating country specific dynamics into the regime switching model leads to a preferred specification based on the log likelihood value and the AIC. Furthermore the absolute value of the average autoregressive parameter is reduced compared to a linear AR(1) model indicating that part of the current account dynamics can be characterized as state persistence showing of in the autoregressive parameters when neglected. State persistence is captured via the state probabilities. The value of 0.886 for p_{00} and 0.904 for p_{11} indicate that both, the sustainable as well as the unsustainable, regimes prevail on average 9-11 years. Furthermore, the alternative MSM specification, where the whole mean is subject to regime shifts, provides similar results, but is not preferred according to AIC or BIC.[11]

The results for the random coefficient specification are given in Table (4.4). Again the Markov Switching specifications are compared to linear autoregressive models. The same pattern arises, i.e. the MSI AR(1) model is the preferred model specification according to the AIC. With respect to the heterogeneity captured via the random coefficients approach, the results for the MS model are somewhat similar to the displayed heterogeneity within the fixed coefficients approach. Interestingly, the persistence within the autoregressive models is higher than in the fixed coefficients specification.[12] Overall, also the random coefficients approach confirms the presence of heterogeneity and characterizes different regimes within the current account balance.

Comparison between reversal episodes identified via ad hoc criteria and those identified via the MSI models is provided in Table (4.5). Based on the description of ad hoc reversals given in Section 2 of this chapter showing that some restriction on the consecutive periods of an identified reversal is necessary to hinder the same reduction in relative deficit to show up twice in the reversal indicator, only ad hoc reversal schemes $I.b$, $I.c$, $II.b$, and $II.c$ will be considered in the following. The main diagonal of Table (4.5) provides the number of reversal episodes identified under a single definition and measurement methodology. Out of a total of 1960 observation at most 193 are classified as reversals according to definition $I.c$ compared to 122 reversal episodes identified under definition $II.c$, which relies on an average reduction of deficit of at least 5%.[13] In general fewer reversal episodes are identified under a regime switching framework. This arises from the ability of the regime switching approach to discriminate eventually between large volatility of current accounts in general and persistent reductions. The upper part of Table (4.5) states the number of reversal episodes commonly identified under ad hoc criteria and regime switching. The seemingly low number of commons is in fact most often due to a different timing. Ad hoc criteria relying on a 3% reduction of current account deficit generally time a reversal episode earlier than the regime switching approach and ad hoc definitions based on an average reduction of at least 5%. For the reversal identified via the regime switching models (lower

[11] Note that a MSI-AR(2) specification does not capture further dynamics as in the linear counterpart.

[12] A possible extension of the considered approach could be concerned with modeling latent country specific heterogeneity via mixture distributions, which would allow more flexibility for modeling the underlying heterogeneity.

[13] The number of time periods is reduced from a total of 2240 to 1960 due the consideration of a maximum of 2 lags within the regime switching models.

right field of Table 4.5) one observes that the inclusion of autoregressive dynamics reduces the number of identified reversals substantially in case of fixed country specific coefficients. Hence, it can be stressed that a consideration of current account dynamics using the full sample information allows to characterize some abrupt movements of the current account on the basis of dynamics, contrary to the case where the regime switching model use only a constant for indicating regime changes, as well as when ad hoc criteria are used for indication of possible reversals. Interestingly, only one reversal is identified on the basis of all identification schemes, which is the current account reversal of Rwanda in 1995. Table (4.5) also gives the number of identified reversals under the random coefficients approach. While the overall number of reversals under the random approach is similar to the number of reversals identified under the fixed coefficients approach, the number of pairwise identified reversals point at differences in identified reversal episodes, which are possibly rooted in the differences of how heterogeneity is considered within the regime switching framework.

Timing differs mostly between 1-2 years, which can be substantial for explaining the occurrence of a reversal. This finding is checked in Table (4.6) via comparison of reversals identified over a time span ranging from $t-2$ to $t+2$, i.e. given a reversal identified under the regime switching approach, the number of reversals identified via use of ad hoc criteria is counted, which are identified in the previous and consecutive two periods. Results in Table (4.6) show in the first four rows, the total number of reversal identified via ad hoc criteria for the periods $t-2$ to $t+2$ given a reversal identified via a regime switching approach in period t. Overall the counted number of reversals show high coverage with the number of reversals identified via regime switching, i.e. almost all reversals identified in period t via regime switching seem to be covered by a reversal episode identified via ad hoc criteria in periods $t-2$ to $t+2$.[14]

Using time varying transition probabilities for investigation of possible explaining factors for reversal bears the problem of possible endogeneity. Several variables discussed in the literature, see e.g. Chinn and Prasad (2003) are itself dependent on current account movements. For example, interest payments as a fraction of gross national income certainly rely on the evolution of current account balance. As in the previous chapters the analysis refers therefore on lagged explanatory variables. The results are presented in Table (4.7). Results are only given for the MSI-AR(1) model as the preferred specification.[15] The set of considered variables contains the following variables; a constant, the US real interest rate (not lagged as a strict exogenous (global) variable), received official transfers, changes in the terms of trade, initial GDP per capita, trade openness, and the current account balance relative to GDP.[16] While US real interest rates serve as a proxy of global investment conditions, initial GDP per capita controls for the stage of economic development. The ratio of official transfers received indicates the dependence of the

[14] With respect to reversals identified under a regime switching model with fixed country specific parameters and no autoregressive component and ad hoc identification scheme $II.b$ even more reversals are counted than the maximum of 112 reversals identified under the regime switching approach. This is owed to the property of ad hoc scheme $II.b$ to identify several reversal episodes in the two periods following an already identified reversal.

[15] Note that the MS model provided similar results.

[16] Note that these variables are chosen as a subset of the variables considered in the previous chapter and the empirical literature, in order to ensure a sufficiently large panel time dimension.

country on foreign transfers to finance its deficits. Connected to this point are changes in the terms of trade as a variable indicating changes in the countries ability to serve its liabilities via export revenues. Trade openness is considered to measure the dependence of the economy on global shocks. Also a more open economy may have more possibilities to realign macroeconomic imbalances. Finally, the level of current account itself is considered as an important factor in the literature, see among others Chinn and Prasad (2003) and Milesi-Ferretti and Razin (1998).

The log-likelihood values given in the last row of Table (4.7) indicate via the corresponding LR-test statistic of 33 ($\chi^2_{12;.99} = 28.30$) the joint significance of the variables considered within the transition probabilities at any conventional level. Among the considered variables only initial GDP per capita is estimated insignificantly. Thus more developed countries have no higher probability to revert to more sustainable levels of current account. For all other variables, higher values increase the probability to leave the less sustainable state. Higher US real interest rates and higher trade openness make reverting current account balances more likely, a result which is in line with the results of Milesi-Ferretti and Razin (1998), see also the analysis of the previous chapters. The probability to stay in a more sustainable state is higher, the higher US real interest rates and changes in the terms of trade. Increases in the terms of trade may point at an improved international competitiveness resulting in higher export flows, while higher US real interest rates are possibly linked to healthy global business conditions increasing commodity exports, which are often important for the sample of countries under investigation. Furthermore, higher US real interest rates may cause less capital inflows and more capital outflows, since US treasury bonds provide a more attractive and secure possibility for global investors.

Interestingly, higher official transfers and higher trade openness decrease the probabilities to stay in both, the less sustainable and the more sustainable state of current account. This ambiguity might be rooted on the one hand in the higher exhibition to global shocks (trade openness), on the other hand flows of official transfers can be as such volatile, see Abrego and Ross (2001) and Edwards (2003). Thus received official transfers may cause less state dependence in current account balance. Finally, the higher current account deficits serving as an important determinant of current account reversals in the empirical literature (Dornbusch and Werner, 1994 and Eichengreen et al. 1996), do not increase the probability to leave the less sustainable state of current account. This contrasting result might be due to the explicit consideration of state dependence within the regime switching framework.

Consideration of time varying transition probabilities leads to an identification of reversal episodes, which seem closer to those obtained from the different ad hoc criteria, see Table (4.8). First of all, the size of the data set is shrunken to 983, as not all explanatory variables are available for all countries. All regime switching specifications provide a similar number of identified reversals, which is very close to the number of reversals identified under the ad hoc criteria relying on an at least 5% reduction of current account deficit. Again, only very few reversal episodes are identified under all specifications pointing at differences with respect to timing, see discussion above. These three episodes are Rwanda 1995, Malaysia 1987 and Mexico 1987. The number of commonly identified reversals under two distinct regimes is only modestly ranging from 20% to 40% of the reversals under regime switching, but again a higher number of commonly identified reversals is hindered by the different timings the different approaches provide. The four lowest lines of Table (4.8) show again the number of commonly identified reversal, when the time span $t-2$ to $t+2$ is considered. A high fraction of reversals identified under the regime switching approach are correspondingly identified by ad hoc criteria within the considered time span.

4.4.2 Costs of Reversals

The costs of reversals have been studied several times in the literature, see e.g. Edwards (2004) and Milesi-Ferretti and Razin (1998) providing mixed evidence. These studies have not been primarily concerend on country specific heterogeneity, which may lead to biased estimates of costs. The average cost of a reversal episode in terms of economic growth is given in Edwards (2004) to equal -3.949%, while Milesi-Ferretti and Razin (1998) find no systematic link between crises and growth. Both studies stress that growth experience within the aftermath of a reversal is very heterogenous. Heterogeneity of costs is incorporated within the regime switching approach as for each country the difference between the two states is specifically estimated.

In order to highlight the appropriateness of regime switching models to generate estimates of costs, their performance is compared to linear vector autoregressions. The estimation results are given in Table (4.9). The first two columns provide estimation results from VAR(1) and VAR(2) specifications. The evidence is in favor of the VAR(2) specification according to the log-likelihood value and AIC. The corresponding LR-test statistic is given as 558.5, therefore the critical value is exceeded by far at any conventional level ($\chi_{0.95;100} = 124.9$). Note that this evidence in favor of higher order serial dependence might capture nonlinearities. As a next step, specifications are estimated, where regime switching is only allowed in one of the two equations. This aims at highlighting that nonlinear elements in the relationship arise from both equations. The first two rows of Table (4.9) refer to the mean of the growth equation when the state is recognized as the more unsustainable. The third and fourth row give the mean and standard deviation across countries succeeding a shift in state. The difference between the mean values suggests that one can distinguish states of high growth from those periods, where a lower growth path is achieved. This specification also provides a remarkable gain in terms of the log likelihood value. A similarly large log likelihood gain is provided by the specification, where the regime switching is only part of the current account equation. Also for the current account, the regime switching approach allows to distinguish a state of higher deficits from a state of lower deficits or small surplus. Both Markov–Switching specifications are estimated in the form with constant transition probabilities. One can note that the states for the growth equations are generally more stable than the states for the current account.

Specifying a common state process for both equations leads to an improved log-likelihood value, on which basis this specification is preferred. Also the information criterion AIC is in favor of this specification, whereas the Schwarz information criterion favors the specification with regime switching in only one equation. The joint modeling of regime switches leads to higher differences between the mean values of both equations. Also, regimes seem to stabilize, especially the regime which corresponds to a more sustainable level of current account.

As a measure for reversal costs the difference between the two states is used. The average growth reduction is 4.86%, which exceeds the cost estimate obtained from a panel treatment by Edwards (2004) by 1%. This difference is characterized by the fact that the regime switching models explicitly take the dynamics into account, whereas the treatment models can be viewed more as a one period effect given the occurrence of crises. Consistent with this interpretation is the estimated expected regime duration of the more sustainable regime, which is the regime after a reversal and therefore incorporates the adjustment process. The estimated expected duration is approximately 3.88 years. On the other hand the median growth reduction between the two states is 3.13%, which is smaller than the estimate of Edwards (2004). Hence one may deduce that the distribution of costs among countries is not symmetric. Furthermore, the inter quartile range is given in row 19 of Table (4.9). 50% of the growth reduction lie between 0.03% and 7.79%. Equivalently, for 25% of all countries no growth reduction is found, whereas the largest 25% reductions of growth exceed 8%. Hence, the phenomenon of current account reversal shows very heterogenous impact of the growth path of a country, which has sofar not been reported within the literature.

The dependency between economic growth and current account balance shall be illustrated graphically for some countries. Figures (4.2) and (4.3) show the paths of current account balance (green), GDP growth (blue) and the states identified by the MS–VAR model. The upper left panel of Figure (4.2) shows the data for Panama. The model identifies 1987 as a reversal episode. The large reduction of current account deficits goes along with a break down of growth performance in 1987 and even more pronounced in 1988. The adjustment already ends in 1989 when current account balance moves into deficit and growth tends back to a positive level. The development for the well studied case of Indonesia, see e.g. Chauvet and Dong (2004), is graphed in the upper right panel. The large reduction of deficits is accompanied with a detoring growth rate. Further and not fully captured by the regime switching approach, the growth path stabilizes again in 1999, whereas the current account balance stays in surplus. The adjustment process seems to produce a third state for the economy which is mutually different from the state of the economy before and during the reversal. The case of Haiti is given in the lower left panel. The reduction of deficit is comparably small, in contrast to the large reduction of growth over the period 1992–1995. The adjustment process for Haiti coincides with the estimated average duration of the more sustainable phase within the relationship. The experience of Malaysia is depicted in the lower right panel of Figure (4.2). In 1998 the current account of Malaysia went up and the growth slowed down. Within the 1980ies the model classifies 1988 as a reversal, but this does not correspond to a typical pattern of growth and current account as documented in 1998. However, the relationship of current account and economic growth seems to be in a third state, not captured by the model setup. Figure (4.3) shows the state of the current account growth relationship for Brazil (upper left), Lesotho (upper right), Hungary (lower left) and Rwanda (lower right). The evidence for these countries is mixed. While for Brazil, the typical pattern is identified by the model, the model fails in the case of Hungary to identify a reversal, which seems to have occurred in 1991. Furthermore, the case of Lesotho exhibits a pattern of current account and economic growth, which makes it hard to be explained via a regime switching process. Also, the case of Rwanda, which is the only reversal episode, commonly identified by all approaches, the pattern is atypical, as the current account deficit decreases after the growth has reduced substantially. A comparison of commonly identified reversals given in Table (4.10) reveals that the model specification with a joint regime switching for economic growth and current account identifies the most reversals commonly with the ad hoc criteria and also provides roughly the same number of reversals in total. Note that when regime switching is identified within the current account equation alone, the number of reversals is substantially reduced. This indicates that the correlation with the growth equation influences the identification process.

4.5 Summary

Identifying current account reversals via Regime Switching models yields several differences compared to using reversal definitions. First of all, the volatility of each country is accounted for by allowing for country specific variance and mean parameters. Hence, less reversals are identified as large fluctuations of current account balances are not linked to reversal episodes. Second, the use of regime switching models provides a unique timing compared to the diverse timings provided by the different ad hoc criteria. Additionally, the state probabilities seem to be influenced by the same set of variables discussed in the empirical literature, with differences referring to the explicit consideration of state dependence within the dynamic behavior of the current account balance.

Finally, within a MS-VAR approach the interaction of current account state and economic growth is assessed. Estimation results show a large average reduction of GDP across countries, when a change in current account state is observed. Therefore the results of Chapter 4 are confirmed. Nevertheless, the findings also document how heterogenous the growth reduction across countries is, as for a quarter of countries no effect of a reversal is identified (Note that more than a quarter of countries do not experience a reversal at all). Summarizing, regimes switching models allow to characterize Current Account Reversals adequately under consideration of the large diversity and provide insights into the determinants of Current Account Reversals and the interaction with economic growth.

Possible extensions could be concerned with alternative possibilities to incorporate heterogeneity within this model, eventually along model based clustering considered by Frühwirth-Schnatter and Kaufmann (2008).

4.6 Technical Details

Estimation via the EM-Algorithm and Simulated Maximum Likelihood

The log-likelihood of the sample can be constructed out of the log likelihood for each panel member as panel members are assumed to be independent. The log-likelihoods of each panel member can be further decomposed into log-likelihoods of each observation of an individual at time t conditional on the past history of the panel member. Hence, this allows to compute the log likelihood of each panel member recursively. Note that the parameters ruling the transition probabilities within the log likelihoods for each panel member are the same for all panel members. This feature allows to estimate panel regime switching models when only few observations are available for each panel member.

First, the derivation of the log likelihood is reviewed for the univariate regime switching model of current account balance. Different specifications of transition probabilities are considered, namely constant transition probabilities proposed by Hamilton (1989) and time varying transition probabilities as in Filardo (1994). Also, the EM-algorithm is extended to cover the VAR approach as well.

Filtering and Smoothing algorithm for estimation procedures

Consideration of a switching intercept only simplifies the calculation compared to alternative specifications, e.g. when also an independent regime switch in the variance is allowed. The reason is that within this specification only the period $t-1$ contains information for period t. Therefore, the Filter algorithm of Hamilton (1989, 1990) consists out of 5 Steps. The derivation is presented in terms of a single individual.

Step I Compute

$$\Pr(S_t = s_t, S_{t-1} = s_{t-1}|Y_{t-1}, \theta) = \Pr(S_t = s_t|S_{t-1} = s_{t-1})\Pr(S_{t-1} = s_{t-1}|Y_{t-1}, \theta),$$

where $\Pr(S_t = s_t|S_{t-1} = s_{t-1})$ denotes the transition probability for period t given the state in period $t-1$ and $\Pr(S_{t-1} = s_{t-1}|Y_{t-1}, \theta)$ has to be initialized within the first iteration of the algorithm or is taken from Step V respectively.

Step II Compute the joint density of $y_t, S_t = s_t, S_{t-1} = s_{t-1}$ conditional on Y_{t-1}, θ as

$$\begin{aligned} f(y_t, S_t &= s_t, S_{t-1} = s_{t-1}|Y_{t-1}, \theta) = \Pr(S_t = s_t, S_{t-1} = s_{t-1}|Y_{t-1}, \theta) \\ & \quad f(y_t|S_t = s_t, S_{t-1} = s_{t-1}, Y_{t-1}, \theta), \end{aligned}$$

where $f(y_t|S_t = s_t, S_{t-1} = s_{t-1}, Y_{t-1}, \theta)$ denotes a normal density given as

$$f(y_t|S_t = s_t, S_{t-1} = s_{t-1}, Y_{t-1}, \theta) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{ -\frac{1}{2\sigma^2} \left(y_t - \mu_{s_t} - \sum_{l=1}^{L} \phi_l y_{t-l} \right)^2 \right\}.$$

Step III Compute the density of y_t unconditional on the states s_t and s_{t-1}, i.e.

$$f(y_t|Y_{t-1},\theta) = \sum_{s_t=0}^{1}\sum_{s_{t-1}=0}^{1} f(y_t, S_t = s_t, S_{t-1} = s_{t-1}|Y_{t-1},\theta).$$

This probability allows to obtain the log likelihood for one panel member.

Step IV Compute

$$\Pr(S_t = s_t, S_{t-1} = s_{t-1}|Y_t,\theta) = \frac{f(y_t, S_t = s_t, S_{t-1} = s_{t-1}|Y_{t-1},\theta)}{f(y_t|Y_{t-1},\theta)}.$$

Step V Compute

$$\Pr(S_t = s_t|Y_t,\theta) = \sum_{s_{t-1}=0}^{1} \Pr(S_t = s_t, S_{t-1} = s_{t-1}|Y_t,\theta),$$

which is used as an input for Step I.

The above given Hamilton Filter is used for likelihood evaluation of the random effects model. The likelihood is hence computed conditional on draws from the marginal distribution of the the random coefficients. The simulated equivalent of the log-likelihood is therefore given as

$$\tilde{\ell}(Y_{IT};\theta) = \sum_{i=1}^{N} \log\left(\frac{1}{R}\sum_{r=1}^{R}\prod_{t=S(i)}^{T(i)} f(y_{it}|Y_{i,t-1},\theta^{(r)})\right),$$

where $S(i)$ denotes the first observation of panel member i and $T(i)$ the last. Random draws are obtained from the assumed unconditional distributions of the random coefficients. Note that the algorithm has to be used sequentially for each panel member.

The smoothed state probabilities used for identification of reversals are obtained using the algorithm of Kim (1994). This algorithm is also essential for the estimation of the fixed coefficients model based on the EM-algorithm. Smoothed state probabilities are obtained recursively from period $T-1 \to 1$.

Step I Compute for all t:

$$\Pr(S_{t+1} = s_{t+1}|Y_t) = \sum_{s_{t+1}=0}^{1} \Pr(S_{t+1} = s_{t+1}|S_t = s_t)\Pr(S_t = s_t|Y_t,\theta),$$

where the second term of the summand is given as the outcome of Step V of the Hamilton Filter.

Step II Use the probabilities computed in Step I and compute for $t : T-1 \to 1$,

$$\Pr(S_t = s_t|Y_T) = \sum_{s_{t+1}=0}^{1} \frac{\Pr(S_{t+1} = s_{t+1}|S_t = s_t)\Pr(S_t = s_t|Y_t)}{\Pr(S_{t+1} = s_{t+1}|Y_t)}\Pr(S_{t+1} = s_{t+1}|Y_T).$$

The application of the EM-algorithm for parameter estimation leads to two maximization steps. The first step is concerned with the estimation of the mean and variance parameters and builds upon the joint conditional density of the data given the smoothed state probabilities representing expected states, while the second steps assess the parameters governing the state probabilities given the expected states summarized within the smoothed state probabilities. For constant transition probabilities the maximization is a linear problem. Given the result of the maximization steps, the expectations step is performed, which is given via the above stated smoothing algorithm of Kim (1994).

Smoothed state probabilities for the random coefficient specifications are calculated via simulation. Given the estimates of parameters obtained via Simulated Maximum Likelihood, trajectories from the unconditional distributions of random parameters are drawn. For each trajectory of random coefficients, the Kim smoothing algorithm as described above is run, and the arithmetic mean average serves as an estimate of smoothed states probabilities.

The estimation of a Markov Switching VAR model follows in principle the described procedure for the univariate model with constant and time varying transition probabilities. All steps of the algorithm can be used analogously. Differences occur only in Step III, where the density is now bivariate and $y_t = (gr_t, ca_t)$ refers to growth and current account balance. Therefore

$$f(y_t|S_t = s_t, S_{t-1} = s_{t-1}, Y_{t-1}, \theta) = (2\pi)^{-1} |\Sigma_i|^{-\frac{1}{2}} e^{\left\{-\frac{1}{2}\left(y_t-\mu_{s_t}-\sum_{l=1}^{L}\Phi_l y_{t-l}\right)'\Sigma_i^{-1}\left(y_t-\mu_{s_t}-\sum_{l=1}^{L}\Phi_l y_{t-l}\right)\right\}},$$

where μ_{s_t} comprises the intercepts of both equations. Within the analysis, the regime switching is also modeled only within the growth and current account equation. Thus, one element of the vector μ_{s_t} is not state dependent.

Tab. 4.1: List of variables - Chapter 4

Mnemonic	Source	Variable Description
ca	WDI	Current account to GDP ratio
gr	WDI	annual real GDP growth
US real int.	WDI	US real interest rate p.a.
Δ TT	WDI	changes in terms of trade index (2000=100)
openness	WDI	trade in % of GDP
GDP per capita	WDI	real GDP per capita
official transfers	GDF	official net transfers to GDP ratio

Notes: The data used in this chapter are taken from the World Development Indicators Database (WDI) or the Global Development Finance Database (GDF). A short note with respect to the construction of some variables is given. The data ranges from 1970 to 2003, but often data is available since 1980 for most of the countries.

Tab. 4.2: Number of commonly identified reversals under different ad hoc criteria

	$I.a$	$I.b$	$I.c$	$II.a$	$II.b$	$II.c$
$I.a$	437	206	222	276	151	142
$I.b$	–	206	82	151	151	69
$I.c$	–	–	222	120	51	114
$II.a$	–	–	–	276	151	142
$II.b$	–	–	–	–	151	69
$II.c$	–	–	–	–	–	142
all			34			
# of observations	2240	2240	2240	2240	2240	2240

Notes: Reversals refer to a reduction of deficits; (all) gives the number of reversals identified under all schemes; $(I.a)$ – refers to a 3% reduction of average current account over a period of three years with no restrictions on current account dynamics $(I.b)$ – refers to a 3% reduction of average current account over a period of three years where no reversals are allowed in the consecutive two years $(I.c)$ – refers to a 3% reduction of average current account over a period of three years when the maximum deficit after the reversal is below the minimum deficit before the reversal $(II.a)$ – refers to a 5% reduction of average current account over a period of three years with no restrictions on current account dynamics $(II.b)$ – refers to a 5% reduction of average current account over a period of three years where no reversals are allowed in the consecutive two years $(II.c)$ – refers to a 5% reduction of average current account over a period of three years when the maximum deficit after the reversal is below the minimum deficit before the reversal.

Tab. 4.3: Maximum likelihood estimates for MS models – fixed effects

		con	AR(1)	AR(2)	MS	MSI-AR(1)	MSM-AR(1)
$\{\mu_{1i}\}$	$\overline{\mu_1}$	-5.0701	-2.5457	-2.6653	-9.6030	-5.1524	-7.2494
	σ_{μ_1}	5.0595	2.9536	3.0272	8.0576	4.7410	6.6481
$\{\mu_{2i}\}$	$\overline{\mu_2}$	–	–	–	0.0901	0.4885	-0.2589
	σ_{μ_2}	–	–	–	6.8451	7.6334	11.5560
$\{\sigma_i^2\}$	$\overline{\sigma^2}$	42.3445	27.4504	26.0210	18.5795	17.8848	17.9962
	σ_{σ^2}	55.7527	37.3482	35.3928	24.5124	23.4575	23.4134
$\{\rho_{1i}\}$	$\overline{\rho_1}$	–	.4834	.5330	–	0.2982	0.3038
	σ_{ρ_1}	–	.2357	.2750	–	0.2627	0.2657
$\{\rho_{2i}\}$	$\overline{\rho_2}$	–	–	.0886	–	–	–
	σ_{ρ_2}	–	–	.1940	–	- -	–
p_{00}		–	–	–	0.8931	0.8376	0.8376
p_{11}		–	–	–	0.9008	0.9156	0.9175
log-lik.		-6619.9	-6158.5	-6105.3	-6224.0	-6053.2	-6057.3
AIC		6.0604	5.7353	5.7734	5.7954	5.7288	5.7325
BIC		6.5488	6.4678	6.7501	6.5330	6.7106	6.7143

Notes: Sample averages of the country specific Maximum Likelihood estimates are reported. Standard deviations correspond to in sample heterogeneity of estimates.

Tab. 4.4: Simulated Maximum likelihood estimates for MS models – random effects

		con	AR(1)	AR(2)	MS	MSI-AR(1)	MSM-AR(1)
$\{\mu_{1i}\}$	μ_{μ_1}	-5.0932 (0.3113)	-1.3771 (0.1691)	-1.3604 (0.1655)	-10.1287 (0.3649)	-1.7737 (0.2253)	-6.9268 (1.0859)
	σ_{μ_1}	4.7042 (0.3009)	0.8751 (0.1504)	0.6830 (0.1288)	6.8585 (0.3725)	0.7601 (0.1165)	1.0029 (0.2259)
$\{\mu_{2i}\}$	$\mu_{\mu_2} - \mu_{\mu_1}$	–	–	–	5.3060 (0.6863)	1.2500 (0.5287)	3.0736 (1.6037)
	$\sigma_{\mu_2-\mu_1}$	–	–	–	5.9255 (0.6778)	0.1307 (0.1538)	2.5154 (0.6920)
$\{\sigma_i\}$	μ_σ	1.5967 (0.0549)	1.4169 (0.0564)	1.4295 (0.0558)	1.1496 (0.0394)	1.3824 (0.0620)	1.4918 (0.0569)
	σ_σ	0.5504 (0.0416)	0.5518 (0.0350)	0.5387 (0.0276)	0.6483 (0.0336)	0.6663 (0.0521)	0.6529 (0.0427)
$\{\rho_{1i}\}$	μ_{ρ_1}	–	0.6346 (0.0255)	0.6337 (0.0254)	–	0.6384 (0.0245)	0.6146 (0.0239)
	σ_{ρ_1}	–	0.1034 (0.0239)	0.1025 (0.0233)	–	0.0959 (0.0254)	0.1651 (0.0305)
$\{\rho_{2i}\}$	μ_{ρ_2}	–	–	0.0063 (0.0220)	–	–	–
	σ_{ρ_2}	–	–	0.0464 (0.0432)	–	–	–
p_{00}		–	–	–	0.8965 (0.0133)	0.7637 (0.1428)	0.7021 (0.1050)
p_{11}		–	–	–	0.9189 (0.0114)	0.9626 (0.1207)	0.9473 (0.0338)
log-lik.		-6999.5	-6530.1	-6529.9	-6775.5	-6511.3	-6512.3
AIC		6.2309	5.8168	5.8149	6.0351	5.8019	5.8028
BIC		6.2410	5.8372	5.8301	6.0555	5.8273	5.8283

Notes: Simulated Maximum Likelihood estimates are reported. Asymptotic standard errors are given in parentheses.

Tab. 4.5: Comparison of identified reversal episodes - I

						MS – smoothed					
						fixed			random		
		I.b	*I.c*	*II.b*	*II.c*	MS	MSI AR(1)	MSM AR(1)	MS	MSI AR(1)	MSM AR(1)
	I.b	186	70	133	58	63	39	39	29	20	24
	I.c	–	193	41	95	22	10	10	22	10	17
	II.b	–	–	133	58	22	10	10	22	10	17
	II.c	–	–	–	122	21	15	15	15	14	15
fixed	MS	–	–	–	–	112	58	57	22	26	23
	MSI AR(1)	–	–	–	–	–	93	88	27	31	21
	MSM AR(1)	–	–	–	–	–	–	92	41	31	24
random	MS	–	–	–	–	–	–	–	84	36	15
	MSI AR(1)	–	–	–	–	–	–	–	–	68	30
	MSM AR(1)	–	–	–	–	–	–	–	–	–	73
all		1									
	# of obs.	1960									

Notes: Ad hoc definitions are the same as in Table 4.2

Tab. 4.6: Checking the differences in timing of identified reversal episodes

	MS – smoothed state probabilities					
	fixed			random		
	c	MSI AR(1)	MSM AR(1)	c	MSI AR(1)	MSM AR(1)
	sum of identified reversals identified over time range $t-2$ to $t+2$					
I.b	131	86	85	82	41	70
I.c	103	70	72	67	43	66
II.b	103	70	72	67	43	66
II.c	79	54	55	51	41	51
	contemporaneously identified reversals					
I.b	63	39	39	29	20	24
I.c	22	10	10	22	10	17
II.b	22	10	10	22	10	17
II.c	21	15	15	15	14	15
	ad hoc reversals identified one period later					
I.b	23	19	18	24	4	27
I.c	13	9	9	10	4	15
II.b	13	9	9	10	4	15
II.c	9	5	4	11	3	11
	ad hoc reversals identified one period earlier					
I.b	21	11	11	12	10	3
I.c	33	25	25	12	9	16
II.b	33	25	25	12	9	16
II.c	29	19	19	11	7	12
	ad hoc reversals identified two periods later					
I.b	7	8	8	10	1	14
I.c	13	11	13	10	3	11
II.b	13	11	13	10	3	11
II.c	8	6	8	7	3	8
	ad hoc reversals identified two periods earlier					
I.b	17	9	9	7	6	2
I.c	22	15	15	13	17	10
II.b	22	15	15	13	17	10
II.c	12	9	9	7	14	7

Notes: Ad hoc definitions are the same as in Table 4.2

Tab. 4.7: Simulated Maximum likelihood estimates for regime switching models with time varying state probabilities

	MSI-(1)		MSI-(2)	
	β_0	β_1	β_0	β_1
constant	3.1115 (0.4067)	−0.1400 (0.5297)	10.5896 (1.0273)	−23.8594 (0.9914)
US real int.	–	–	−1.0775 (0.2137)	4.9544 (0.3255)
official transfers	–	–	−0.1206 (0.0437)	−0.5692 (0.2325)
Δ TT	–	–	−0.0065 (0.0055)	0.1260 (0.0693)
GDP per capita	–	–	0.0831 (0.3753)	0.6043 (0.4759)
openness	–	–	−1.8705 (0.9957)	−2.6127 (1.0432)
current account ratio	–	–	−0.5363 (0.2160)	0.5267 (0.2599)
μ_{μ_1}	−1.4481 (0.2241)		−2.0485 (0.2531)	
σ_{μ_1}	0.5821 (0.2152)		0.8045 (0.1962)	
$\mu_{\mu_2-\mu_1}$	2.4840 (0.9926)		1.9231 (1.0987)	
$\sigma_{\mu_2-\mu_1}$	5.2035 (0.9707)		3.6658 (0.7373)	
μ_σ	0.9737 (0.1000)		1.0347 (0.0969)	
σ_σ	0.6928 (0.0766)		0.6690 (0.0670)	
ρ_μ	0.6618 (0.0539)		0.4330 (0.0492)	
ρ_σ	0.2832 (0.0434)		0.1576 (0.0448)	
log-likelihood	-2287.6		-2271.1	

Notes: Simulated Maximum Likelihood estimates are reported. Asymptotic standard errors are given in parentheses.

Tab. 4.8: Comparison of identified reversal episodes - II

	$I.b$	$I.c$	$II.b$	$II.c$	MSI-AR(1) – random	
					(1)	(2)
$I.b$	102	44	67	35	14	6
$I.c$	–	104	26	40	10	7
$II.b$	–	–	67	35	10	7
$II.c$	–	–	–	56	14	5
	–	–	–	–	29	9
	–	–	–	–	–	26
all	3					
# of obs.	983					
	–	–	–	–	21	16
$\sum_{t-2}^{t+2}$	–	–	–	–	23	19
	–	–	–	–	23	19
	–	–	–	–	21	16

Notes: Ad hoc definitions are the same as in Table 4.2; (1) denotes constant (smoothed) state probabilities corresponding to estimation given in Table (4.4) in column MSI-(1), whereas (2) refers to time varying (smoothed) state probabilities referring to esimation results given in Table (4.4) in column MSI-(2).

Tab. 4.9: Maximum likelihood estimates for MSI-VAR models

		VAR(1)	VAR(2)	MSI-VAR(1) growth	MSI-VAR(1) ca	MSI-VAR(1)
$\{\mu_{10i}\}$	$\overline{\mu_{10}}$	3.566	3.156	3.5317	3.3712	5.3214
	$\sigma_{\mu_{10}}$	3.261	5.067	2.9985	2.8276	3.4365
$\{\mu_{11i}\}$	$\overline{\mu_{11}}$	–	–	1.3149	–	0.4601
	$\sigma_{\mu_{11}}$	–	–	2.8467	–	6.2886
$\{\mu_{20i}\}$	$\overline{\mu_{20}}$	-2.167	-2.346	-1.9807	-2.1132	-4.0871
	$\sigma_{\mu_{20}}$	4.625	5.472	4.5665	4.5501	5.7815
$\{\mu_{21i}\}$	$\overline{\mu_{21}}$	–	–	–	0.2834	-0.0755
	$\sigma_{\mu_{21}}$	–	–	–	6.2772	5.6057
p		–	–	0.9943	0.9765	0.8859
q		–	–	0.6357	0.5245	0.7435
avg. growth red.		–	–	–	–	4.8613
med. growth red.		–	–	–	–	3.128
growth red. IQR		–	–	–	–	$[0.030; 7.794]$
log.-lik.		-3977.5	-3698.2	-2372.0	-2363.0	-2171.3
AIC		9.2462	9.1906	6.1119	6.0936	5.8317
BIC		16.0417	19.0063	13.6864	13.6681	14.1613

Notes: Sample averages of the country specific Maximum Likelihood estimates are reported. Standard deviations correspond to in sample heterogeneity of estimates.

Tab. 4.10: Comparison of identified reversal episodes - III

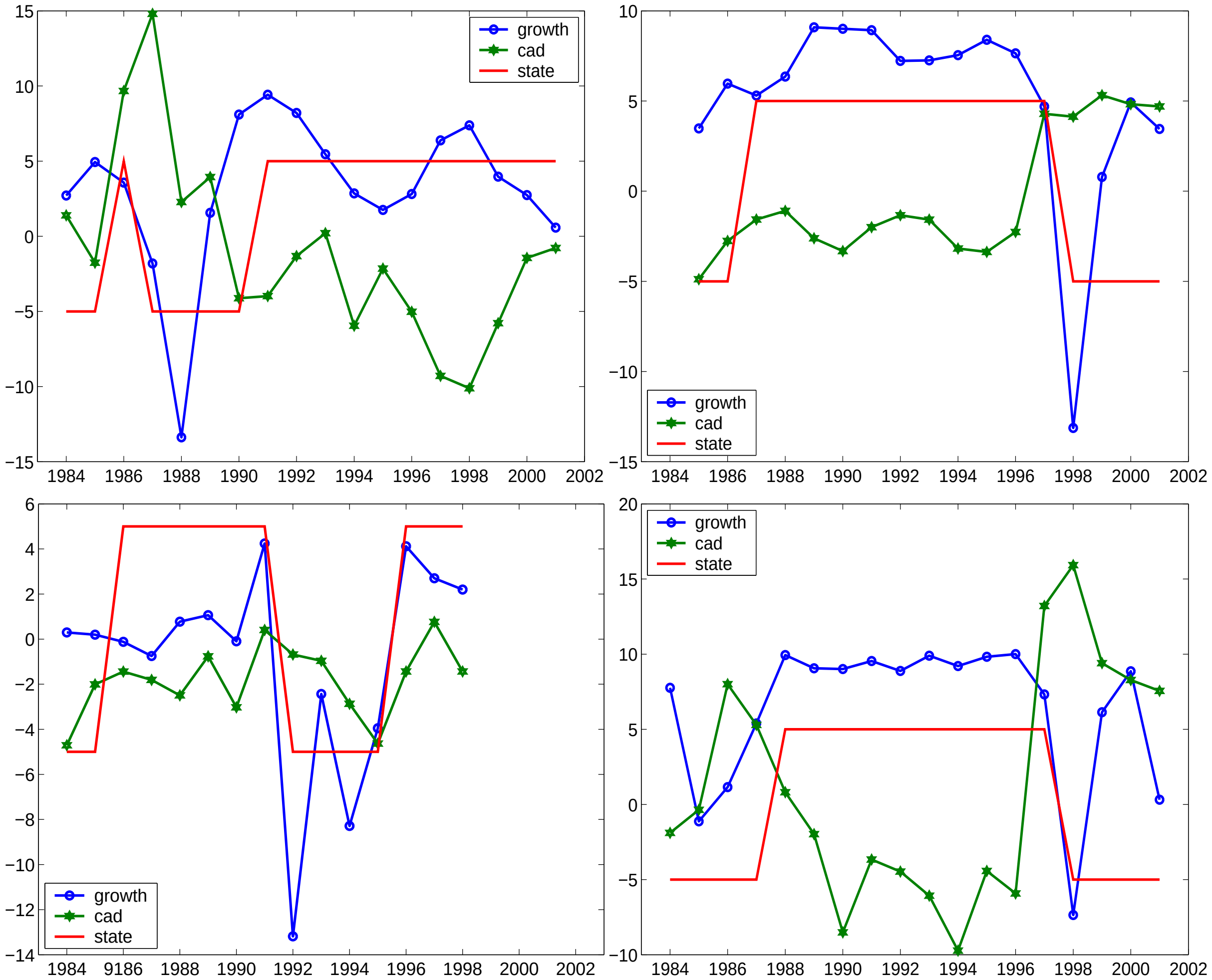
	$I.b$	$I.c$	$II.b$	$II.c$	MSI-VAR(1)		
					smoothed		
					cad	growth	joint
$I.b$	102	44	67	35	4	12	16
$I.c$	–	104	26	40	2	8	14
$II.b$	–	–	67	35	2	8	14
$II.c$	–	–	–	56	3	9	6
	–	–	–	–	11	8	5
smoothed	–	–	–	–	–	50	12
	–	–	–	–	–	–	63
all	0						
# of obs.	983						

Notes: Ad hoc definitions are the same as in Table 4.2; the category cad (growth) refer to a model, where only the current account equation (growth equation) is subject to regime shifts, whereas the category joint denotes the model refers to a model where regimes shifts within both equations of the MS-VAR model are governed by a single Markov process.

Fig. 4.1: Current account reversals identified via ad hoc criteria

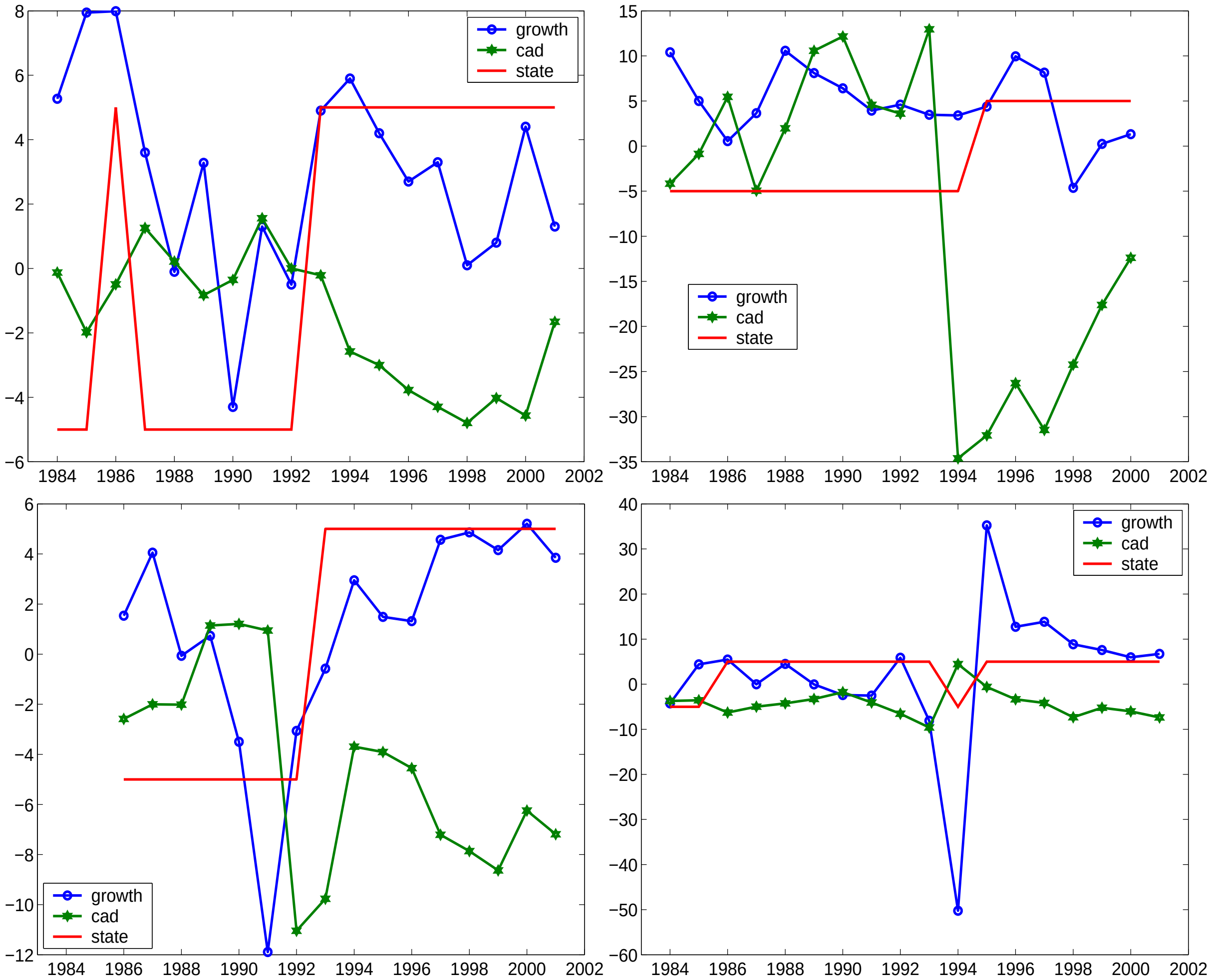
Notes: The upper left panel shows the Current Account Balance relative to GDP for Swaziland; the upper right panel for Bhutan; the middle left to Paraguay; the middle right to Jordan; the lower left for Venezuela; the lower right for Jamaica. ◇ refers to relative current account deficit; *o* (lower lines) refer to ad hoc reversals identified via a 3% reduction; + (upper lines) refer to the identified ad hoc criteria reversals using a 5% reduction.

Fig. 4.2: Relationship of current account balance and economic growth I



Notes: The upper left panel shows the estimated states, the relative current account balance and economic growth for Panama; the upper right panel refers to Indonesia; the lower left panel shows the results for Haiti; and the lower right panel for Malaysia.

Fig. 4.3: Relationship of current account balance and economic growth II



Notes: The upper left panel shows the estimated states, the relative current account balance and economic growth for Brazil; the upper right panel refers to Lesotho; the lower left panel shows the results for Hungary; and the lower right panel for Rwanda.

5. CONCLUSION

This thesis aims at an empirical analysis of the determinants and costs of crises connected to the current account balance. The analysis provides a review of empirical results documented in the literature based on empirical specifications concerned about the incorporation of latent country specific heterogeneity and serial dependence structures. Inclusion of structures capturing latent heterogeneity and serial dependence into the considered non linear empirical frameworks is necessary, in order to provide valid statistical inference. The employed random coefficient approach deals with the incidental parameter problem arising from fixed effects estimation in the considered panels providing only a relative short time dimension. Three frameworks are analyzed in detail in this thesis.

Chapter 2 shows the application of Bayesian methodology in Probit and Treatment frameworks. The Bayesian approach allows a flexible handling of latent country specific heterogeneity and serial correlation. In specific, this chapter establishes Gibbs sampling schemes for the Probit and Treatment framework accounting for latent heterogeneity and serial correlation. The estimation results indicate the presence of country specific heterogeneity via Bayesian specification tests, which allow the comparison of the non nested model specifications. Robustness of some reversal determinants is found, when latent heterogeneity is considered. Incorporation of latent heterogeneity also considerably improves the models ability to reidentify and predict the observed reversals. The treatment analysis shows that costs in terms of economic growth are possibly overestimated, when latent heterogeneity within the country's growth dynamics and the reversal determinants is neglected. The Bayesian estimation procedure is based on MCMC techniques to generate draws from the joint posterior distribution of the parameters. The inspection of the posterior distribution and moments thereof allows to assess the significance of estimates without relying on asymptotic arguments.

In the following Chapter 3, analysis has focused on an intertemporal relationship between currency crises and current account reversals. The relationship is motivated from the detected interaction between the two crises indicators of these events. The necessity to explicitly account for this relationship arises from the assessment of the effects crises exhibit on economic growth, where neglect of this relationship would result in biased estimates. In order to ensure the numerical accuracy of estimates in the presence of state dependence and latent country specific heterogeneity, an Efficient Importance Sampling procedure has been developed, which accounts for these typical features often documented for macroeconomic panel data. The developed sampler builds upon the GHK importance sampler and via consideration of latent heterogeneity extends the range of considered applications of Efficient Importance Sampling algorithms in this field. The model reveals that currency crises and current account reversals both have negative effects on economic growth. Currency crises increase the probability of current account reversals in the next period, while both types of crises reduce their own occurrence probability in the next period. These intertemporal dependencies are incorporated in the assessment of the effect, crises exhibit on growth over time. The simulated growth pathes conditioned on the occurrence of a particular crisis show the longer lasting and larger impact of current account reversals on growth compared to the effect of currency crises.

Chapter 4 also provides an assessment of the gains in numerical precision concerning the integration involved in Maximum Likelihood estimation provided by the developed Efficient Importance Sampling procedure. The results reveal the necessity to consider the Efficient Importance Sampling for reduction of the involved simulation error in order to assess the parameter uncertainty via standard tests correctly for a given set of (pseudo) random draws involved in integration.

While the Bayesian analysis of Chapter 2 points at a possible overestimation of reversal costs when latent heterogeneity is neglected, the likelihood estimates of Chapter 3 provide strong evidence in favor of costs linked to both crises, which are also influenced by country specific characteristics. These differences may be caused by the two distinguishing features of the two analyses. The analysis in Chapter 3 extends the analysis of Chapter 2 as it controls via consideration of intertemporal dependence between both crises indicators a possible source of mispecification. Furthermore, not all explaining variables considered in Chapter 2 have been available for the considered sample of countries in particular for the period 1975-1980, thus making the use of different sets of explanatory variables necessary.[1] Also the incorporation of parameter uncertainty within the Bayesian framework may contribute to differences in the estimates of costs. Both frameworks suggest however that the assessment of costs of crises asks for a cautious specification of country specific heterogeneity.

Chapter 4 provides an alternative approach to the analysis of current account reversals in terms of a regime switching framework. This alternative framework allows to assess whether ad hoc criteria conceptualized for identification of reversals deliver crises episodes similar to those, which are identified under a fully specified statistical process for the dynamic behavior of the relative current account balance. The adapted Markov-Switching model allows for country specific heterogeneity and takes differences across countries into account concerning the dynamics and volatility of the current account balance. The difficulty to assess the uncertainty of estimates within the fixed coefficients framework has been overcome by setting up a random coefficients approach, which also allows to analyze a set of variables explaining regime switches considered within the literature. The results point at differences concerning the timing of reversal episodes. In order to allow for an assessment of costs within the regime switching framework, an extension towards a vector autoregressive setup has been considered. The differences between regimes governing the growth equations provide similar costs of reversals compared to those documented in the empirical literature and the previous chapters of this thesis. Further attempts could

[1] The data sets employed are different with respect to the considered time ranges. Since the currency crises indicator is available for the period 1975-1997, current account reversals occurring between 1998 and 2002 are not included in Chapter 4, since they are available only for the shorter time horizon considered in Chapter 3.

aim at an analysis of more parsimonious forms of heterogeneity within this extended empirical framework.

The analysis provided in this thesis aims at an assessment of the impact the incorporation of latent heterogeneity and serial dependence structures has on the estimation of costs involved in the occurrence of crises connected to the balance of payments. The analysis based on ad hoc identification schemes of these crises in Chapter 2 and Chapter 3 document the importance to account for latent heterogeneity via random coefficients. Bayesian and likelihood based specification tests indicate that specifications incorporating latent heterogeneity are to be preferred against pooled specifications. Furthermore, while the Bayesian analysis in Chapter 2 points at an overestimation of reversal costs when latent heterogeneity is neglected, Chapter 3 points out the importance to consider simultaneously the effect of currency crises as an important predictor of current account reversals. The joint consideration of currency crises and current account reversals reveals costs in terms of economic growth for both crises phenomena. Chapter 4 provides an alternative approach to identification and classification of reversal episodes. The performed analysis reveals costs of current account reversals similar to those documented by the estimated trivariate treatment model.

The considered possibilities to incorporate serial dependence and latent country specific heterogeneity into several empirical frameworks provide encouraging results. The modeling of latent heterogeneity can hence serve as a benchmark model for alternative approaches concerned with the incorporation of latent heterogeneity.

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Mitgliedschaften

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Publikationsliste

Veröffentlichungen in referierten Fachzeitschriften

- The Decline in German Output Volatility: A Bayesian Analysis, Empirical Economics, mit J. Hogrefe und R. Liesenfeld, erscheint demnächst
- Dynamic multi-sector CGE modeling and the specification of capital: Comment on Farmer and Wendner (2004), 2009, Structural Change and Economic Dynamics 20, 74-75, (mit J. Hogrefe)

Arbeitspapiere

- Determinants and Costs of Current Account Reversals under Heterogeneity and Serial Correlation, Economic Working Paper No. 2007-17
- Analysis of Current Account Reversal via Regime Switching Models, Working Paper, mit J. Hogrefe
- Reproducing Business Cycle Features in Germany: An Evaluation for the Need of Non-Linear Models, with J. Hogrefe
- Assessing the Costs of Currency Crises and Current Account Reversal on Economic Growth, Economic Working Paper No. 2008-01
- Bayesian Approaches to Social Network Analysis, Technical Report, with J. Mumm
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