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Determinants and Costs of Current Account Reversals under Heterogeneity and Serial Correlation

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Abstract

Recent empirical evidence suggests that reversing current account balances imply costly adjustment processes leading to reduced economic growth. Using large panel data sets to analyze determinants and costs of reversals asks for controls of heterogeneity among countries. This paper contributes a Bayesian analysis, which allows a parsimonious yet flexible handling of country specific heterogeneity via random coefficients. Furthermore, the analysis allows for serially correlated errors in order to capture persistence within the employed macroeconomic data. Bayesian specification tests provide evidence in favor of models incorporating heterogeneity and serial correlation. The results suggest that consideration of serial correlation and heterogeneity is necessary to assess correctly the determinants and costs of reversals. Results are checked for robustness against the underlying reversal definition.

JEL classification: C30; F32; F43; C33; C35

Keywords: Current account reversals; Bayesian Analysis; Panel Probit Model; Panel Treatment Model; Random Parameters; Serial Correlation

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1 Introduction

Costly current account adjustment processes succeeding changes in the world capital movements have been subject to several studies in the 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 readjustments of 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) 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 suggests no systematic reduction of growth in the period after a current account reversal. Using a treatment model Edwards (2004) analysis the costs of a reversal. His results are at odds to those of Milesi-Ferretti and Razin (1998) and suggest that a current account deficit reduces economic growth on average by four percentage points and 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 methodologies are less concerned with 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 capture not 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 is nevertheless problematic. Some countries do not experience a current account reversal, thus country specific fixed effects are not identified within the probit framework. While for the treatment model a fixed effects approach is in principle applicable within the growth equation, estimation in short panels possibly causes an incidential parameter problem. Hence, alternative approaches to deal with unobserved country specific heterogeneity are necessary in order to assess correctly the determinants and costs of reversals.

The aim of this paper is therefore to analyze the 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 sofar often classifies countries into regions, see e.g. Edwards (2004), to allow for heterogeneity between this specific regions. Random coefficients offer a more flexible, yet parsimonious form of heterogeneity, which is analyzed in this paper. Next to analyzing the determinants of reversals via a mixed probit model, this paper 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 within the errors is considered. Such an approach allows to account for persistence in unobserved components, a feature likely present in the context of macroeconomic event studies as argued by Falcetti and Tudela (2006).

The contribution of this paper is 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 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.[1] 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

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

Carlo (MCMC) technique namely Gibbs sampling is employed. This approach allows to inspect the properties of heterogeneity among countries, as Gibbs sampling 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 via comparing of the marginal likelihoods, which are computed according to the methodology proposed by Chib (1995). Furthermore it is highlighted in this paper 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 outline of the paper is as follows. Section 2 describes the data and provides some information on the theoretical background of current account reversals. The specifics of the alternative reversal identification schemes are also presented. The frameworks with and without heterogeneity and serial correlation of the probit and treatment model are presented in Section 3. Within this section also the applied Bayesian estimation techniques is described. Section 4 presents the empirical findings. Section 5 concludes.

2 Data, Theoretical Background and Reversal Identification

Data is constructed using 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 out 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.[2] The number of observations per country does 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

[2]The following list of countries are analyzed: Argentina, Bangladesh, Benin, Bolivia, Botswana, Brazil, Burkina Faso, Burundi, Cameroon, Central African Republic, Chile, China, Colombia, Congo. Rep., Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt. Arab Rep., El Salvador, Gabon, Gambia, The, Ghana, Guatemala, Guinea-Bissau, Haiti, Honduras, Hungary, India, Indonesia, Jordan, Kenya, Lesotho, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Morocco, Niger, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Rwanda, Senegal, Seychelles, Sierra Leone, Sri Lanka, Swaziland, Thailand, Togo, Tunisia, Turkey, Uruguay, Venezuela, RB, Zimbabwe.

paragraphs will 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 $t-1$.

Macroeconomic variables included 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.

As *external* variables are included 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 structural features captured by the above variables have on the ability of a country 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. Interest payments relative to GDP are included in order to indicate the liabilities a country have 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 banks stock of reserves result inevitably in a balance-of-payments crises. Changes in the terms of trade may anticipate changes in trade flows. The analytic model of Tornell and Lane (1998) analyze the effect of terms of trade shocks on current account balance. Their model suggests that positive terms of trade shock can result in a deterioration of current account 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 crises even when macroeconomic policies of a country are consistent.

Current account reversals are defined using several ad hoc criteria.[3] 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 applied 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 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%. 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. Scheme (III/IV) differs from scheme (I/II) only with respect to the shift magnitude of average current account balance triggering a reversal, which has to exceed 5% now. The numbers of reversals identified under the alternative identification schemes are reported in Table (1). Entries on the main diagonal provide the number of identified reversals for the four alternative schemes, whereas the other entries provide the number of reversals which

[3] Identifying reversals is therefore not data driven as proposed by Bagnai and Manzocchi (1999) who use structural break tests for identification of reversals.

are jointly identified by alternative schemes. In total, the data summarizes 1312 time periods, as three year averages are considered. When all identifications schemes are applied simultaneously only 53 reversals are identified from a maximum number of 127 reversals under scheme I. 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.

3 Model Description and Estimation

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 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 samplers employed in estimation are shortly reviewed and the methods for comparing the different specifications are introduced.

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

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

where δ_{it} indicates the occurrence of a reversal identified under the different identification schemes for each individual $i = 1, \ldots, N$ 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

$$\delta^*_{it} = X_{it}\beta + e_{it}, \tag{2}$$

where e_{it} is an 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 an iid country specific random variable with common mean b and covariance matrix W_b for all countries, i.e.

$$\beta_i \overset{\text{iid}}{\sim} \mathcal{N}(b, W_b), \quad i = 1, \ldots, N. \tag{3}$$

Note that W_b can also be diagonal assuming independence of the random coefficients. Inclusion of random parameter heterogeneity induces a heteroscedastic error over time for each individual. Consider the 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

$$X_{i\cdot} W_b X'_{i\cdot} + I, \tag{4}$$

where I is an identity matrix denoting the covariance matrix of the latent errors $e_{i\cdot}$. 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 mean vector b provides insight into the relationship between determinants and reversals when heterogeneity among countries is taken into account.

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

$$\delta^*_{it} = X_{it}\overline{\beta} + X^{\text{ran}}_{it}\beta_i + e_{it}, \tag{5}$$

where superscript $^{\text{ran}}$ refers to the variables assigned a random coefficient and $\overline{\beta}$ denotes the constant parameters. Hence, the probability of a country i being at time t in the observed state δ_{it} is conditional on $\beta_i, \overline{\beta}$

$$P_{it|\beta_i,\overline{\beta}} = \Phi\left((2\delta_{it} - 1)(X_{it}\overline{\beta} + X^{ran}_{it}\beta_i)\right), \tag{6}$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution. Given the probability $P_{it|\beta_i,\overline{\beta}}$ the likelihood can be stated as

$$L(\cdot|\overline{\beta}, b, W_b) = \prod_{i=1}^{N} \int_{\beta_i} \left(\prod_{t=S(i)}^{T(i)} P_{it|\overline{\beta},\beta_i} \right) f(\beta_i|b, W_b) d\beta_i, \tag{7}$$

where $S(i)$ denotes the first and $T(i)$ the last available period for country i.

Serial correlation can be introduced in two forms. It can be implemented via the error components of the latent model. Alternatively, lagged values of the latent δ^*_{it} can be included as explanatory variables. In both forms one needs the unconditional distribution of $\delta^*_{iS(i)}$ that is for the first period observed for individual i. This is unproblematic 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 unconditional moments of $\delta^*_{iS(i)}$. Note that this problem can also 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[4]

$$e_{it} = \rho e_{it-1} + u_{it}, \tag{8}$$

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

$$\Omega_i = \{\omega_{hj}\}, \quad h, j : \{T(i) - S(i) + 1 \times T(i) - S(i) + 1\}, \quad \omega_{hj} = \frac{\rho^{|h-j|}}{1-\rho^2}. \tag{9}$$

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

$$P_{i\cdot|\beta_i,\overline{\beta}} = \int_{d(\delta_{iS(i)}, X_{iS(i)}, \overline{\beta}, \beta_i)} \cdots \int_{d(\delta_{iT(i)}, X_{iT(i)}, \overline{\beta}, \beta_i)} \Psi(e_{iS(i)}, \ldots, e_{iT(i)}) de_{iS(i)} \ldots de_{iT(i)}, \tag{10}$$

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

$$d(\delta_{it}, X_{it}, \overline{\beta}, \beta_i) = \begin{cases} (-\infty, -(X_{it}\overline{\beta} + X^{\text{ran}}_{it}\beta_i)), & \text{if } \delta_{it} = 0, \\ (-(X_{it}\overline{\beta} + X^{\text{ran}}_{it}\beta_i), \infty) & \text{if } \delta_{it} = 1. \end{cases} \tag{11}$$

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

$$L(\cdot|\overline{\beta}, b, W_b, \rho, X) = \prod_{i=1}^{N} \int_{\beta_i} P_{i\cdot|\beta_i,\overline{\beta}} \cdot f(\beta_i|b, W_b) d\beta_i, \tag{12}$$

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

3.1.1 Bayesian Estimation

The Bayesian estimation approach via Gibbs sampling, see Albert and Chib (1993), allows a flexible handling of the discussed model features. The high dimensionality of the likelihood integral provides another argument in favor of MCMC methods, as they are well suited for high dimensional integration.[5] In a Bayesian setup the joint posterior of the parameters is hence proportional to

$$p(\overline{\beta}, b, W_b, \rho|X, \delta) \propto L(\delta|\overline{\beta}, b, W_b, \rho, X)\pi(\overline{\beta}, b, W_b, \rho), \tag{13}$$

[4] Preliminary analysis suggests that one lag sufficiently covers the serial correlation.

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

where $\pi(\overline{\beta}, b, W_b, \rho)$ denotes the prior distribution of the model parameters. Parameter estimates are obtained via the realizations of the moments and quantiles of the posterior distribution. The significance of a parameter estimate is assessed via the 95% highest density region of a posterior distribution. The implemented 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. 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 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 Appendix C.

The implemented Gibbs sampler generates draws from the joint posterior of the models via 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 $\{\{e_{it}\}_{t=S(i)}^{T(i)}\}_{i=1}^{N}$. 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 Appendix A. The algorithm has hence the following structure:

(i) Simulate from $f_i(\{e_{it}\}_{t=S(i)}^{T_i}|\overline{\beta}, \beta_i, \{X_{it}, \delta_{it}\}_{t=S(i)}^{T_i}, \rho)$ $i : 1 \rightarrow N$, 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 (11). Given the sampled errors one can compute the latent variable $\delta_{it}^* = X_{it}\overline{\beta} + X_{it}^{\text{ran}}\beta_i + e_{it}$. This linearization of the setup follows Albert and Chib (1993).

   - Given the sequences of the error terms, simulate from $f(\rho|\{\{e_{it}\}_{t=S(i)}^{T(i)}\}_{i=1}^{N})$, which is a truncated normal distribution arising from the equation $e_{it} = \rho e_{it-1} + u_{it}$.

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

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

After providing the Gibbs sampler for the employed probit model, the treatment model allowing for serial correlation and heterogeneity shall be introduced.

3.2 Treatment Model

A theoretical link between current account reversal as a balance of payments crises 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 crises in 1994 and the Asian crises in 1998 have provided several channels for a contractionary effect. According to Dornbusch et al. (1995), a current account reversal may cause a disruption in the growth process as it brings an end to an inconsistent macroeconomic policy often linked to inflation reduction. Others like Chang and Velasco (1998) and Radelet and Sachs (1998) argue that increasing foreign borrowing causes illiquidity making the countries more vulnerable to panic and sudden loss of confidence, see for a detailed discussion Moreno (1999).

Measuring the effect of current account reversals on economic growth shall be done within a treatment model. Since Heckman (1978) established Maximum Likelihood estimation of the corresponding simultaneous equation framework for continuous and discrete endogenous variables, this framework has also been subject of Bayesian analysis, see among others Angrist et al. (1996). Following Edwards (2004), joint consideration of growth and current account reversals within a treatment model allows to take the possible correlation between shocks causing changes in the probability of a reversal and growth into account. The purpose of this analysis to assess the costs of reversals under a general form of heterogeneity and serial correlation tries to match the fact that reversal episodes in different countries often show different characteristics, although they are often stemming from the dilemma of a lack of credibility and inflation inertia, which is a common feature of developing countries, see Calvo and Vegh (1999) for an overview.

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

$$gr_{it} = Z_{it}\alpha + \epsilon_{it}, \tag{14}$$

$$\delta^*_{it} = X_{it}\beta + e_{it}. \tag{15}$$

Within Z_{it} the binary reversal indicator δ_{it} is included to capture the effect of a reversal on growth. The effect on growth is correspondingly measured as $E[gr_{it}|Z_{it},\delta_{it}=1] - E[gr_{it}|Z_{it},\delta_{it}=0]$. The set of explanatory variables in both equations contains the variables described in Section 2.

Again, unobserved heterogeneity of countries stemming from unobserved characteristics shall be incorporated. Random coefficients within the growth equation capture differences between countries with respect to growth dynamics. As in the probit model this is achieved via random coefficients within each equation, i.e.

$$\alpha_i \sim \mathcal{N}(a, W_a), \qquad \beta_i \sim \mathcal{N}(b, W_b). \tag{16}$$

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

$$gr_{it} = \overline{Z}_{it}\overline{\alpha} + Z_{it}^{\text{ran}}\alpha_i + \epsilon_{it}, \tag{17}$$

$$\delta_{it}^* = \overline{X}_{it}\overline{\beta} + X_{it}^{\text{ran}}\beta_i + e_{it}. \tag{18}$$

Serial correlation is incorporated within the error terms of the probit regression. Hence

$$e_{it} = \rho e_{it-1} + u_{it}, \tag{19}$$

and

$$\begin{pmatrix} \epsilon_{it} \\ u_{it} \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \psi \\ \psi & 1 \end{pmatrix}\right). \tag{20}$$

This form of error structure leads to correlation between past shocks of the growth equation and contemporaneous shocks of the probit equation. Consideration of such correlation allows the latent process of the reversal to be linked to the history of shocks hitting the growth process, which are possibly not adequately represented by the included explaining variables. The likelihood contribution of country i as a constituent part of the posterior distribution is given by the integral:

$$L_i(\cdot|a, b, W_a, W_b, \sigma, \psi, \rho, \overline{\alpha}, \overline{\beta}) = \int_{\alpha_i}\int_{\beta_i} \Psi_1(\cdot)\left(\int \cdots \int \Psi_{2|1}(\cdot) de_{iS(i)} \ldots de_{iT(i)}\right) f(\alpha_i, \beta_i) d\alpha_i d\beta_i. \tag{21}$$

$\Psi_1(\cdot)$ denotes the marginal distribution of $\epsilon_{i\cdot}$ evaluated at $gr_{i\cdot} - Z_{i\cdot}\alpha_i$ and $\Psi_{2|1}(\cdot)$ the conditional distribution of $e_{i\cdot}|\epsilon_{i\cdot}$ with corresponding conditional mean and conditional variance. Given this model setup, the next section will shortly provide the Gibbs sampler of this model.

3.2.1 Bayesian Estimation

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

(i) Simulate from $f_i(\{e_{it}\}_{t=S(i)}^{T(i)}|\alpha_i, \beta_i, \{X_{it}, Z_{it}, gr_{it}, \delta_{it}, \epsilon_{it}\}_{t=S(i)}^{T(i)}, \sigma^2, \psi, \rho, a, W_a, b, W_b)$ $i : 1 \rightarrow N$, which is similar to Step (i) described for the probit model. Nevertheless, here it is derived from a multivariate truncated normal conditional on the observed errors $\epsilon_{i\cdot}$ form 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 $f_i(\alpha_i, \beta_i|\{X_{it}, Z_{it}, gr_{it}, \delta_{it}^*\}_{t=S(i)}^{T(i)}, \sigma^2, \psi, \rho, a, W_a, b, W_b, \overline{\alpha}, \overline{\beta})$, $i : 1 \rightarrow N$, 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 hyperparameters 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 $f(\overline{\alpha}, \overline{\beta}|\{X_{it}, Z_{it}, gr_{it}, \delta_{it}^*\}_{t=S(i)}^{T(i)}, \sigma^2, \psi, \rho, a, W_a, b, W_b, \{\alpha, \beta_i\}_{i=1}^N)$, which is 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 normalized to 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). 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. 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

$$\begin{pmatrix} \sigma^2 & \psi \\ \psi & 1 \end{pmatrix} = \begin{pmatrix} \xi + \psi^2 & \psi \\ \psi & 1 \end{pmatrix}. \tag{22}$$

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.[6]

The next section deals with comparison of the different specifications.

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

3.3 Model Comparison

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). A more general introduction is provided by Kass and Raftery (1995). Starting point of the derivation is to decompose the log marginal likelihood into

$$\ln m(S) = \ln L(\theta^*|S) + \ln \pi(\theta^*) - \ln p(\theta^*|S). \tag{23}$$

As this identity holds for all θ, it is calculated at a point within the highest density region where θ^* is the posterior mean.

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. The algorithm consists of the following steps.

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

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

$$\tilde{L}_i = \frac{1}{M} \sum_{m=1}^{M} \prod_{t=S(i)}^{T(i)} \xi(e_t^{(m)}|e_{-t}^{(m)}, \beta_i^{(m)}), \tag{24}$$

where $\xi(e_t|e_{-t})$ denotes the corresponding univariate truncated normal distribution being 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 (12). For the treatment model the GHK-simulator provides an estimate for the likelihood of one country i corresponding to Equation (21) via

$$\tilde{L}_i = \frac{1}{M} \sum_{m=1}^{M} \xi_{\epsilon_{i\cdot}}(\alpha_i^{(m)}) \left(\prod_{t=S(i)}^{T(i)} \xi_{e_{i\cdot}|\epsilon_{i\cdot}}(e_t^{(m)}|e_{-t}^{(m)}, \beta_i^{(m)}, \alpha_i^{(m)}) \right), \tag{25}$$

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

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

$$p(\theta^*|S) = p(\theta_1^*|S) \cdot p(\theta_2^*|\theta_1^*, S) \cdot \ldots \cdot p(\theta_k^*|\theta_k^*, \theta_{k-1}^*, \ldots, \theta_1^*, S).$$

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.

$$\tilde{p}(\beta|S) = \frac{1}{M} \sum_{m=1}^{M} f(\beta^*|\delta^{*(m)}, S), \tag{26}$$

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 Appendix A and B 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 Jeffrey's (1962), which classifies the log Bayes factor as the difference between two log marginal likelihoods.[7]

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. To obtain a simple closed form of this probability, it is calculated as follows

$$\frac{1}{M} \sum_{m=1}^{M} p(\delta_{it} = 1|\overline{X}_{it}\overline{\beta}^{(m)} + X_{it}^{\mathrm{ran}(m)}\beta_i^{(m)} + \rho^{(m)}e_{it-1}^{(m)}). \tag{27}$$

Thus all information available a time time t via regressors, parameters and latent errors is included, such that this probability is a byproduct of the Gibbs sampler. When the estimated probability

[7] 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 $B \geq 4.6$.

exceeds 0.5 an observation is classified as a reversal.[8] The ratio of correct and misclassified reversals serves as a model selection criterion. As all explaining variables X_{it} provide only information up to period $t-1$, this probability highlights the models capabilities to predict a reversal although the parameters and latent variables are obtained using the full sample information.

4 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. The impact of reversals on economic growth is analyzed via treatment regressions. The robustness of findings is checked for different reversal identification schemes as described in Section 2. 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.[9]

4.1 Determinants of Current Account Reversals

The estimates for four probit specifications incorporating serial correlation and heterogeneity at different degrees will be discussed. Starting point is the pooled panel probit model given in Equations (1) and (2). The next specification accounts for serial correlation as stated in Equation (8). Afterwards, no serial correlation in the errors, but random coefficients modeling country specific heterogeneity described in Equation (3) are considered. Finally, a specification incorporating both serial correlation in the errors and random coefficients is estimated.

Table (3) reports the results for the pooled panel specification obtained by Bayesian estimation. The upper part of Table (3) contains the set of *macroeconomic* variables, which display low explanatory power across all reversal schemes. Only the variable government expenditures becomes

[8]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.

[9]All empirical results presented below were broadly confirmed using Maximum Likelihood Estimation. The estimation was 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 yielded 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.

significant for reversal scheme I and III respectively. Neither mean growth rate, nor 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 solving imbalances via reversals are less connected to the macroeconomic state of an economy but to its external. This is underlined by the estimation results of the *external* variables given in the middle part of Table (3). A higher current account deficit raises significantly the probability to experience a reversal. 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 often provided by institutional lenders 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 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 (3). 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 therefore seem to trigger only adjustment processes spanning several years.

The results for the specification accounting for serial correlation are given in Table (4). 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 imply a strict restriction on the two consecutive periods after a reversal. Note that the correlation parameter is not significant within scenario IV. This pattern might be due to to the different restriction on the aftermath of a reversal implied by the different reversal schemes. Table (10) summarizes the log marginal likelihoods for all estimated model specifications. 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. According to Falcetti and Tudela (2006) accounting for serial correlation is important in order to allow for possible intertemporal linkages between crises. Constraints moderating the occurrence of a reversal may be altered once a country experienced a reversal in the past. Also persistent unobserved heterogeneity can be captured by serial correlated errors. 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 modeled via 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 external variables only, which show a low ratio of variance between countries to total variance. These variables are the mean current account deficit, the level of reserves and official transfers.[10] Bayesian estimates are given in Table (5). The findings with respect to the macroeconomic and global variables are unchanged when compared to the two former specifi-

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

cations. Again the importance of the external variables is underlined. The estimated variances of the three random coefficients range from 0.021 to 0.045 implying a considerable degree of heterogeneity, which will be discussed in detail below. Interestingly via consideration of a random coefficients in connection to the official transfers, this variable becomes overall significant. In contrast, the variable concessional debt becomes insignificant over all reversal schemes. Note that concessional debt 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 depend on unobserved heterogeneity. Unobserved heterogeneity alters also the influence of interest payments which is now significantly positive for reversal scheme III. Bayes factors provide overall reversal schemes strong to very strong evidence in favor of incorporation of unobserved heterogeneity via random coefficients compared to the two former specifications.[11] 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. 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. This influence might differ as for some countries the reserves are managed by central banks with a varying degree of independence from politics.

Finally, a more parsimonious specification allowing for heterogeneity and serially correlated errors including only the external variables is estimated. This specification illustrates that only few variables are needed to identify the actually observed reversals, see Table (11) and discussion below. Bayesian estimation results can be found in Table (6). All external variables show similar behavior and significance as in the above specifications. The estimated serial correlation is again positive for reversal scheme I and III, while negative for reversal scheme II and IV. According to the marginal likelihood, this parsimonious specification is to be preferred against the other ones. This stresses the importance of country specific heterogeneity and the external variables 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 (27). Table (11) gives the number of identified reversals

[11] Note that this specification of heterogeneity is also strongly preferred against inclusion of regional dummies within the pooled specification capturing region specific heterogeneity. The corresponding marginal likelihoods for the different reversal schemes are -393.23, -322.74, -302.10 and -247.13.

under the four considered model specifications. While in reversal scheme I the pooled specification gets 10 out of 100 reversals 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 incorrect. 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 on the pooled specification. This confirms also 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.

Furthermore, Bayesian estimation allows to access the form of country specific heterogeneity contained within the panel data set. Figure (1) shows the distribution of the sampled country specific coefficients for the mean CAD 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, heterogeneity and serial correlation affect 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.

4.2 Costs of Reversals

The relationship between economic growth and current account reversals established in the third generation models of balance-of-payments crises 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 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 (14) and (15). Afterwards, the relationship is investigated allowing for serial correlation in the probit equation (Equation 19). Finally, results for a specification incorporating heterogeneity via random coefficients, Equation (16-18), 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 (7). 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 shocks affect jointly both growth and the occurrence probability of a reversal.

In the growth equation several variables which are also considered within the probit equation function as covariates. For instance, openness is considered as an explaining factor for economic growth, as well as investment 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 estimated costs within the pooled specification given by the reversal dummy range from 6.99 for the second reversal scheme to 4.56 for reversal scheme IV, which is at the upper end of the costs reported in the literature. Following Edwards (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 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 the results concerning the determinants of reversals are in line with those obtained in the probit regressions. All variables have expected signs, with minor changes in the reached significance level for some variables.

Estimation results of the treatment model incorporating serial correlation within the probit equation are given in Table (8). Similar to the results of the probit specifications, serial correlation is significant 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. Further, the magnitude of the serial correlation is reduced significantly, when compared to the probit estimations, as the imposed correlation structure allows 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, but not significantly. Differences in all other estimated parameters are negligible. Comparison of the marginal likelihood reveals strong evidence for inclusion of serial correlation within reversal scheme I, while no or only weak evidence is found in reversal schemes II to IV.

The simultaneous consideration of heterogeneity and serial correlation is based on a slightly more parsimonious specification of the probit equation focusing on the external variables.[12] Heterogeneity in the probit equation is again connected to the current account deficit, the level of reserves and the concessional debt. Within the growth equation random coefficients are assigned to the constant and the lagged growth rate. This allows for country specific dynamics of growth, which is likely present due to institutional differences as argued by Lee et al. (1998). Estimation results are given in Table (9).

The findings with respect to costs of reversals and the correlation between the two equations differ substantially compared to the other treatment specifications. Estimated costs of a reversal become insignificant and are substantially reduced for all reversal schemes and also no significant correlation between the two model equations can be found. Allowing for a country specific growth process alters therefore the results concerning the impact of current account reversals on economic growth. Furthermore, the parameter capturing the influence of investment is no longer significantly estimated. These variables therefore seem to have captured some heterogeneity, which is now present within the random coefficients. The marginal likelihood indicates that including heterogeneity via random coefficients is the preferred model structure, see Table (10). This underlines the importance to consider heterogeneity in order to measure the costs of a reversal correctly. In order to check the findings against robustness against the underlying prior assumptions concerning the variance of the random coefficients, the results were checked for two alternative prior scenarios, see Table (1), see lines • and ••. The estimated costs and correlation parameters were similar across the different prior specifications and the marginal likelihood given in Table (10) indicate strong evidence in case of all priors for inclusion of heterogeneity via random coefficients. The determinants of current account reversals behave similar compared to the previous specifications and no evidence is found for a systematic link between costs and trade openness.

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. Moreover incorporation of random coefficients is the preferred model. 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 under

[12]Note that results have been checked also for the full specification revealing similar results. The log marginal likelihoods are given in Table (10), line full.

for the treatment model incorporating serial correlation and heterogeneity are comparable (2%-4%) the incorporation of parameter uncertainty renders estimated costs insignificantly for all reversal schemes.

5 Conclusion

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 and thus hence leaving a fixed effects approach unidentified. The Bayesian framework offers also a 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 reversal correctly. Results for the probit regressions suggests that inclusion of serial correlation is necessary to account for the correlation pattern induced via the different reversal definitions. 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 is not depending on the current account deficit although the estimated mean effect is highly significant. A possible explanation may arise from the different institutional backgrounds of the countries, which are hardly accessible via observable variables. Furthermore, via the incorporation of heterogeneity the model's ability to indicate the observed variables is improved. Heterogeneity and serial correlation therefore provides 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 heterogeneity modeled via random coefficients is neglected. The sample selection found in the pooled specifications is not present when country specific dynamics is allowed. Thus, within the preferred model specification, no significant negative effect of current account reversal on economic growth is detected. Also more open countries seem not to suffer less from a reversal than more closed economies. As the evidence provided by the analysis is in favor of accounting for heterogeneity, further attempts should aim on linking heterogeneity to observed variables.

References

[1] Albert, J., H., and Chib, S. Bayesian analysis of binary and polychotomous response data. *Journal of the American Statistical Association 88*, 422 (1993), 669–679.

[2] Alesina, A., and Perotti, R. Fiscal Adjustments in OECD countries: Composition and Macroeconomic Effects. *IMF Staff Papers*, 44 (1997), 210–248.

[3] Angrist, J., Imbens, G. and Rubin, D.B. Identification of causal effects using instrument variables. *Journal of the American Statistical Association 91* (1996), 444–455.

[4] Ansari, M. I. Sustainability of the US Current Account Deficit: An Econometric Analysis of the Impact of Capital Inflow on Domestic Economy. *Journal of Applied Economics VII*, 2 (2004), 249–269.

[5] Atkeson, A., and Rios-Rull, J.-V. The balance of payments and borrowing constraints: An alternative view of the mexican crises. *Journal of International Economics 41* (1996), 331–349.

[6] Bagnai, A., and Manzocchi, S. Current-account reversals in developing countries: The role of fundamentals. *Open economies review*, 10 (1999), 143–163.

[7] Bolduc, D., Fortin, B. and Fournier, M. Multinomial probit estimation of spatially interdependent choices: An empirical comparison of two new techniques. *International Regional Science Review*, 20 (1997), 77–101.

[8] Börsch-Supan, A., and Hajivassiliou, V. A. Smooth unbiased multivariate probability simulators for maximum likelihood estimation of limited dependent variable models. *Journal of Econometrics 58* (1993), 247–368.

[9] Calvo, G. *Emerging markets in turmoil: Bad luck or bad policy?* MIT Press, 2005.

[10] Calvo, G. A. Capital markets and the exchange rate with special reference to the dollarization debate in latin america. *Journal of Money, Credit and Banking 33*, 2 (2001), 312–334.

[11] Calvo, G. A. Explaining sudden stops, growth collapse and bop crises: The case of distortionary output taxes. *NBER Working Paper Series*, 9864 (2003).

[12] Calvo, G. A., and Mendoza, E. Mexico's balance-of-payments crisis: A chronicle of death foretold. *International Finance Discussion Papers 545* (1996).

[13] Calvo, G. A., and Vegh, C. A. *Inflation Stabilization and BOP Crises in Developing Countries*, vol. 1. Elsevier Science, 1999, ch. 24, pp. 1531–1614.

[14] Calvo, G., Izquierdo, A. and Talvi, E. Sudden stops, the real exchange rate, and fiscal sustainability: Argentina's lessons. *NBER Working Paper Series*, 9828 (2003).

[15] Cashin, P., and McDermott, C. J. Are Australia's Current Account Deficits Excessive? *IMF Working Papers 96*, 85 (1996).

[16] Chang, R., and Velasco, A. The asian liquidity crises. *NBER Working Paper*, 6796 (1998).

[17] Chib, S. Marginal likelihood from the gibbs output. *Journal of the American Statistical Association 90*, 432 (1995), 1313–1321.

[18] Chinn, M. D., and Prasad, E. S. Medium-term determinants of current accounts in industrial and developing countries: an empirical exploration. *Journal of International Economics 59* (2003), 47–76.

[19] Cole, H. L., and Kehoe, T. J. Self-fulfilling debt crises. *Review of Economic Studies 67* (2000), 91–116.

[20] Dornbusch, Rudiger, Goldfayn, Ilan and Valdes, Rodrigo O. Currency crises and collapses. *Brookings Papers on Economic Activity*, 2 (1995), 219–293.

[21] Edwards, S. Financial openness, sudden stops, and current-account reversals. *American Economic Review 94*, 2 (2004), 59–64.

[22] Falcetti, E., and Tudela, M. Modelling currency crises in emerging markets: A dynamic probit model with unobserved heterogeneity and autocorrelated errors. *Oxford Bulletin of Economics and Statistics 68*, 4 (2006), 445–471.

[23] Fischer, S., and Frenkel, J. A. *Economic Growth and Stages in the Balance of Payments.* New York: Academic Press, 1974, pp. 503–521.

[24] Flood, R., and Garber, P. Collapsing exchange rate regimes: Some linear examples. *Journal of International Economics 17* (1984), 1–13.

[25] Geweke, J. *Computing Science and Statistics: Proceedings of the Twenty-Third Symposium on the Interface.* Fairfax: Interface Foundation of North America, Inc., 1991, ch. Efficient Simulation from the Multivariate Normal and Student-t Distributions Subject to Linear Constraints, pp. 571–578.

[26] Geweke, J., and Keane, M. *Compuationally Intensive Methods For Integration in Econometrics, Handbook of Econometrics*, vol. 5. Elsevier Science B.V., 2001, ch. 56, pp. 3463–3568.

[27] Geweke, J., Keane, M. and Runkle, D. Alternative computational approaches to inference and in the multinomial probit model. *Review of Economics and Statistics 76* (1994), 609–632.

[28] Haberler, G. Integration and growth of the world economy in historical perspective. *The American Economic Review 54*, 2 (1964), 1–22.

[29] Hajivassiliou, V. Smooth simulation estimation of panel data ldv models. *Department of Economics, Yale University* (1990).

[30] Halevi, N. An empirical test of the "balance of payments stages" hypothesis. *Journal of International Economics 1* (1971), 103–117.

[31] Heckman, J. J. Dummy endogenous variables in a simultaneous equation system. *Econometrica 46*, 4 (1978), 931–959.

[32] Hutchison, M. M., and Neuberger, I. Output costs of currency and balance of payments crises in emerging markets. *University of California Santa Cruz Working Paper Series* (2001).

[33] Hyslop, D. R. State dependence, serial correlation and heterogeneity in intertemporal labor force participation of married women. *Econometrica 67*, 6 (November 1999), 1255–1294.

[34] Kaminsky, G. L., and Reinhart, C. M. The twin crises: The causes of banking and balance-of-payments problems. *The American Economic Review 89*, 3 (June 1999), 473–500.

[35] Kass, R. E., and Raftery, A. E. Bayes factors. *Journal of the American Statistical Association 90*, 430 (June 1995), 773–795.

[36] KEANE, M. Computationally practical simulation estimator for panel data. *Econometrica 62*, 1 (1994), 95–116.

[37] KRUGMAN, P. A model of balance of payment crises. *Journal of Money, Credit and Banking 11* (1979), 311–325.

[38] LEE, K., PESARAN, M.,H., AND SMITH, R. Growth empirics: A panel data approach - a comment. *The Quarterly Journal of Economics*, 1 (1998).

[39] MCCULLOCH, R., AND ROSSI, P. E. An exact likelihood analysis of the multinomial probit model. *Journal of Econometrics* (1994), 207–240.

[40] MCCULLOCH, ROBERT E., POLSON,NICHOLAS G. AND ROSSI, PETER E. A Bayesian analysis of the multinomial probit model with fully identified parameters. *Journal of Econometrics 99* (2000), 173–193.

[41] MELECKY, M. The impact of current account reversals on growth in central and eastern europe. *International Finance*, 0502004 (2005).

[42] MILESI-FERRETTI, G. M., AND RAZIN, A. Current account sustainability: Selected east asian and latin american experiences. *NBER Working Paper Series*, 5791 (1996).

[43] MILESI-FERRETTI, G. M., AND RAZIN, A. Sharp reductions in current account deficits: An empirical analysis. *European Economic Review*, 42 (1998), 897–908.

[44] MILESI-FERRETTI, M., AND RAZIN, A. Current account sustainability. *Princeton Studies in International Finance*, 81 (October 1996).

[45] MORENO, R. Depreciation and recessions in east asia. *FRBSF Economic Review*, 3 (1999).

[46] NOBILE, A. Comment: Bayesian multinomial probit models with a normalization constraint. *Journal of Econometrics 99* (2000), 335–345.

[47] OBSTFELD, M. Rational and self-fulfilling balance-of-payments crises. *The American Economic Review 76*, 1 (1986), 72–81.

[48] RADELET, S., AND SACHS, J. D. The east asian financial crises: Diagnosis, remedies, prospects. *Brookings Paper on Economic Activity*, 1 (1998), 1–78.

[49] TORNELL, A., AND LANE, P. R. Are windfall a curse? a non-representative agent model of the current account. *Journal of Inernational Economics 44* (1998), 83–112.

[50] TRAIN, K. E. *Discrete Choice Methods with Simulation.* Cambridge, 2003.

Appendix

The functional forms of the full conditional distributions employed within the Gibbs Samplers are given for the Probit and Treatment model with serially correlated errors and partial random coefficients. Furthermore, the hyperparameters of the prior distributions are given.

A – Probit model with serial correlation and partial heterogeneity via random coefficients

The Gibbs sampler for this model specification consists out of 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 of each full conditional distribution are explicitly given. Define

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

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

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

(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}, $j = 1, \ldots, n^{\mathrm{ran}}$ 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 a prior distribution. Hence

$$\begin{aligned} q_{W_b} &= q_{W_b0} + \sum_{i=1}^N (T(i) - S(i) + 1), \\ S_{W_b} &= q_{W_b0}S_{W_b0} + \sum_{i=1}^N (T(i) - S(i) + 1)\left(\sum_{i=1}^N (\beta_i - b)(\beta_i - b)'\right). \end{aligned}$$

(iv) The serial correlation parameter ρ is obtained via regressing 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 $\mathcal{N}_{\mathcal{T}}(\mu_\rho, \sigma_\rho^2)$, where

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

(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 calculation of

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

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

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

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}. Hence 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

$$\kappa_{i\cdot} = \delta_{i\cdot}^* - X_{i\cdot}^{\text{ran}} \beta_i.$$

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

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

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

B – Treatment model with serial correlation and partial heterogeneity via random coefficients

The Gibbs sampler for this model specification consists of 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

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

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

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

(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

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

$$\Sigma_a = \left(NW_a^{-1} + \Omega_{a0}^{-1}\right)^{-1}.$$

(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

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

$$\Sigma_b = \left(NW_b^{-1} + \Omega_{b0}^{-1}\right)^{-1}.$$

(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. Hence

$$q_{W_a} = q_{W_a0} + \sum_{i=1}^N (T(i) - S(i) + 1),$$

$$S_{W_a} = q_{W_a0}S_{W_a0} + \sum_{i=1}^N (T(i) - S(i) + 1)\left(\sum_{i=1}^N (\alpha_i - a)(\alpha_i - a)'\right).$$

(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. Hence

$$q_{W_b} = q_{W_b0} + \sum_{i=1}^N (T(i) - S(i) + 1),$$

$$S_{W_b} = q_{W_b0}S_{W_b0} + \sum_{i=1}^N (T(i) - S(i) + 1)\left(\sum_{i=1}^N (\beta_i - b)(\beta_i - b)'\right).$$

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

$$\begin{aligned}\zeta_i^1 &= (\eta_{iS(i)}, \ldots, \eta_{iT(i)-1})' \quad \text{and} \\ \zeta_i^2 &= (\eta_{iS(i)+1}, \ldots, \eta_{iT(i)})'.\end{aligned}$$

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

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

(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 parting stemming form 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. Hence

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

where

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

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}. Hence 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

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

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.

C – Specification of Prior Moments

The following Table provides the values of the employed prior moments. $I_{k\times k}$ denotes an identity matrix and $_{\mathrm{ran}}$, $_{\mathrm{fix}}$, $_{\mathrm{ran}_a}$ and $_{\mathrm{ran}_b}$ denote the corresponding number of random coefficients. Robustness of the results concerning the treatment model including serial correlation and random effects are checked using alternative variance priors given in lines • and ••.

Table 1: Prior Distributions

	Probit Model		
(μ_{b0}, Ω_{b0})	$\mathcal{N}$	0	$I_{\text{ran}\times\text{ran}} \cdot 1000$
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\text{ran}}$	$\mathcal{IG}$	5	5
(q_{W_b0}, S_{W_b0})	–	–	–
$(\mu_{\overline{\beta}0}, \Omega_{\overline{\beta}0})$	$\mathcal{N}$	0	$I_{\text{fix}\times\text{fix}} \cdot 1000$
	Treatment Model		
(μ_{a0}, Ω_{a0})	$\mathcal{N}$	0	$I_{\text{ran}_a\times\text{ran}_a} \cdot 1000$
(μ_{b0}, Ω_{b0})	$\mathcal{N}$	0	$I_{\text{ran}_b\times\text{ran}_b} \cdot 1000$
$\{(\alpha_{W_a^{jj}0}, \beta_{W_a^{jj}0})\}_{j=1}^{\text{ran}_a}$	$\mathcal{IG}$	5	5
•	$\mathcal{IG}$	1	1
••	$\mathcal{IG}$	10	10
(q_{W_a0}, S_{W_a0})	–	–	–
$\{(\alpha_{W_b^{jj}0}, \beta_{W_b^{jj}0})\}_{j=1}^{\text{ran}_b}$	$\mathcal{IG}$	5	5
(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	$I_{\text{fix}\times\text{fix}} \cdot 1000$

D – Functional Forms of Densities

In the following the functional forms of the densities employed within the calculation of the posterior are given.

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. *Gamma*:
   Let x be a scalar and $\alpha, \beta > 0$. Then
   $$f_{\mathcal{G}}(x; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} \exp\left(-x\beta\right).$$

3. *Univariate Truncated Normal*:
   Let $x \in [l, u]$ and Φ denote the cumulative density of a standard normal distribution. Then
   $$f_{\mathcal{N}_\mathcal{T}}(x; \mu, \sigma) = \frac{(2\pi)^{-\frac{1}{2}} \sigma^{-1} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right)}{\Phi(\frac{u-\mu}{\sigma}) - \Phi(\frac{l-\mu}{\sigma})}.$$

Table 2: 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 .

Table 3: Pooled probit model - Bayesian estimates

	I	*II*	*III*	*IV*
constant	$\mathbf{-3.2336}^*$ (0.8493)	$\mathbf{-2.4587}^*$ (0.9449)	$\mathbf{-2.4867}^*$ (0.9684)	$\mathbf{-1.8293}$ (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	$\mathbf{0.0233}^*$ (0.0118)	0.0100 (0.0135)	$\mathbf{0.0301}^*$ (0.0133)	0.0173 (0.0153)
		external		
mean CAD	$\mathbf{-0.0609}^*$ (0.0120)	$\mathbf{-0.0457}^*$ (0.0130)	$\mathbf{-0.0525}^*$ (0.0125)	$\mathbf{-0.0416}^*$ (0.0140)
openness	−0.0018 (0.0022)	−0.0012 (0.0024)	0.0002 (0.0024)	0.0003 (0.0027)
reserves	$\mathbf{-0.0784}^*$ (0.0305)	$\mathbf{-0.0553}$ (0.0337)	$\mathbf{-0.1102}^*$ (0.0392)	$\mathbf{-0.1215}^*$ (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)	$\mathbf{-0.0079}$ (0.0047)	$\mathbf{-0.0125}^*$ (0.0053)	$\mathbf{-0.0177}^*$ (0.0063)
interest payments	0.0239 (0.0306)	−0.0020 (0.0350)	0.0529 (0.0332)	0.0188 (0.0372)
terms of trade	$\mathbf{-0.0032}^*$ (0.0017)	$\mathbf{-0.0033}$ (0.0019)	$\mathbf{-0.0075}^*$ (0.0024)	$\mathbf{-0.0063}$ (0.0026)
		global		
US real interest rate	$\mathbf{0.1303}^*$ (0.0532)	0.0673 (0.0600)	0.0523 (0.0593)	0.0246 (0.0671)
OECD growth rate	$\mathbf{0.1413}^*$ (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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 4: Probit model with serial correlation - Bayesian estimates

	I	*II*	*III*	*IV*
constant	**−3.7337****	**−2.4967****	−1.6105	**−1.8703**
	(1.7891)	(0.9110)	(2.5208)	(1.0337)
		macroeconomic		
mean growth rate	0.0058	−0.0066	0.0332	0.0090
	(0.0319)	(0.0224)	(0.0389)	(0.0269)
mean investment	0.0102	0.0079	0.0172	0.0130
	(0.0223)	(0.0113)	(0.0314)	(0.0140)
initial log GDP	0.2105	0.0577	0.0097	0.0282
	(0.1970)	(0.0934)	(0.3007)	(0.1095)
government	0.0100	0.0103	0.0190	0.0196
	(0.0208)	(0.0121)	(0.0250)	(0.0144)
		external		
mean CAD	**−0.0898****	**−0.0460****	**−0.0973****	**−0.0422****
	(0.0235)	(0.0120)	(0.0314)	(0.0135)
openness	−0.0048	−0.0011	0.0002	0.0003
	(0.0047)	(0.0023)	(0.0060)	(0.0026)
reserves	**−0.1646****	**−0.0565**	**−0.2894****	**−0.1241****
	(0.0717)	(0.0313)	(0.1414)	(0.0456)
official transfers	−0.0056	−0.0057	0.0162	0.0125
	(0.0152)	(0.0111)	(0.0189)	(0.0124)
concessional debt	−0.0073	**−0.0084**	**−0.0282**	**−0.0190****
	(0.0085)	(0.0044)	(0.0165)	(0.0065)
interest payments	0.0452	−0.0040	0.0857	0.0105
	(0.0438)	(0.0332)	(0.0536)	(0.0377)
terms of trade	**−0.0076****	**−0.0035**	**−0.0153****	**−0.0064**
	(0.0038)	(0.0018)	(0.0066)	(0.0023)
		global		
US real interest rate	**0.1941**	0.0763	0.1123	0.0326
	(0.0813)	(0.0606)	(0.0984)	(0.0697)
OECD growth rate	0.1343	0.1249	0.0972	0.0825
	(0.0977)	(0.0813)	(0.1161)	(0.0943)
ρ	**0.6390****	**−0.2682****	**0.7263****	−0.2486
	(0.0742)	(0.1203)	(0.0883)	(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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 5: Probit model with partial heterogeneity - Bayesian estimates

	I	*II*	*III*	*IV*
constant	$-\mathbf{3.4913}^{*}$ (1.7002)	$-\mathbf{3.3853}$ (1.7983)	$-\mathbf{3.4977}$ (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 CAD	$-\mathbf{0.2274}^{*}$ (0.0392)	$-\mathbf{0.1583}^{*}$ (0.0371)	$-\mathbf{0.1946}^{*}$ (0.0455)	$-\mathbf{0.1389}^{*}$ (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	$-\mathbf{0.2453}^{*}$ (0.0731)	$-\mathbf{0.2134}^{*}$ (0.0798)	$-\mathbf{0.3493}^{*}$ (0.0966)	$-\mathbf{0.3476}^{*}$ (0.0955)
$\sigma^2_{\text{reserves}}$	0.0384 (0.0144)	0.0346 (0.0143)	0.0454 (0.0226)	0.0377 (0.0177)
official transfers	$-\mathbf{0.1244}^{*}$ (0.0467)	$-\mathbf{0.1536}^{*}$ (0.0521)	$-\mathbf{0.1295}^{*}$ (0.0554)	$-\mathbf{0.1526}^{*}$ (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)	$\mathbf{0.1767}^{*}$ (0.0623)	0.0824 (0.0668)
terms of trade	$-\mathbf{0.0126}^{*}$ (0.0038)	$-\mathbf{0.0095}^{*}$ (0.0038)	$-\mathbf{0.0159}^{*}$ (0.0049)	$-\mathbf{0.0102}^{*}$ (0.0046)
		global		
US real interest rate	$\mathbf{0.1477}^{*}$ (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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 6: Probit model with partial heterogeneity and serial correlation- Bayesian estimates

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

Table 7: 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 CAD	**−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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 8: 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 CAD	**−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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 9: Treatment model with serial correlation and heterogeneity - Bayesian estimates

	I	*II*	*III*	*IV*
σ	4.5420 (0.1123)	4.5919 (0.1266)	4.5323 (0.1106)	4.5434 (0.1129)
ψ/σ	0.1126 (0.1538)	0.3861 (0.2466)	0.0379 (0.1249)	0.1514 (0.1972)
ρ	0.0562 (0.0460)	−0.0293 (0.0490)	0.0432 (0.0473)	−0.0136 (0.0469)
constant	**2.1834** (1.1334)	**2.0265** (1.1457)	**2.1553** (1.1079)	**2.0911** (1.1238)
$\sigma^2_{\text{constant}}$	0.0494 (0.0263)	0.0505 (0.0271)	0.0505 (0.0266)	0.0516 (0.0311)
lagged growth rate	**0.2176*** (0.0436)	**0.2135*** (0.0444)	**0.2190*** (0.0438)	**0.2177*** (0.0438)
$\sigma^2_{\text{lagged growth}}$	0.0401 (0.0110)	0.0409 (0.0110)	0.0400 (0.0109)	0.0399 (0.0109)
reversal	−2.0890 (1.4380)	−3.8804 (2.3037)	−2.6211 (1.5769)	−2.4797 (2.1991)
reversal × openness	0.0064 (0.0132)	−0.0046 (0.0156)	0.0145 (0.0154)	−0.0015 (0.0181)
openness	**0.0092** (0.0052)	**0.0102** (0.0052)	**0.0094** (0.0052)	**0.0105*** (0.0052)
mean investment	0.0205 (0.0241)	0.0233 (0.0243)	0.0215 (0.0245)	0.0206 (0.0241)
initial log GDP	−0.0775 (0.1584)	−0.0569 (0.1625)	−0.0894 (0.1549)	−0.0850 (0.1590)
constant	−0.1828 (0.5947)	−0.3730 (0.5999)	−0.4765 (0.7283)	−0.6061 (0.6680)
		external		
mean CAD	**−0.2155*** (0.0378)	**−0.1522*** (0.0362)	**−0.2067*** (0.0429)	**−0.1448*** (0.0375)
$\sigma^2_{\text{mean CAD}}$	0.0248 (0.0071)	0.0201 (0.0054)	0.0274 (0.0086)	0.0224 (0.0067)
openness	−0.0039 (0.0033)	−0.0009 (0.0033)	0.0004 (0.0037)	0.0007 (0.0036)
reserves	**−0.2598*** (0.0873)	**−0.2452*** (0.0798)	**−0.3757*** (0.1125)	**−0.3564*** (0.1013)
$\sigma^2_{\text{reserves}}$	0.0382 (0.0162)	0.0340 (0.0135)	0.0530 (0.0268)	0.0399 (0.0175)
official transfers	**−0.1156*** (0.0424)	**−0.1304*** (0.0433)	**−0.1548*** (0.0648)	**−0.1469*** (0.0505)
$\sigma^2_{\text{official transfers}}$	0.0262 (0.0084)	0.0250 (0.0080)	0.0329 (0.0118)	0.0287 (0.0092)
concessional debt	−0.0086 (0.0065)	−0.0112 (0.0071)	−0.0070 (0.0094)	−0.0159 (0.0091)
interest payments	0.0675 (0.0460)	0.0049 (0.0512)	**0.1405*** (0.0578)	0.0533 (0.0605)
terms of trade	**−0.0102*** (0.0038)	**−0.0080*** (0.0034)	**−0.0147*** (0.0047)	**−0.0088*** (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 the 90% highest density region does not include zero. Bold figures with * indicate the 95% highest density region does not include zero.

Table 10: Log Marginal Likelihoods

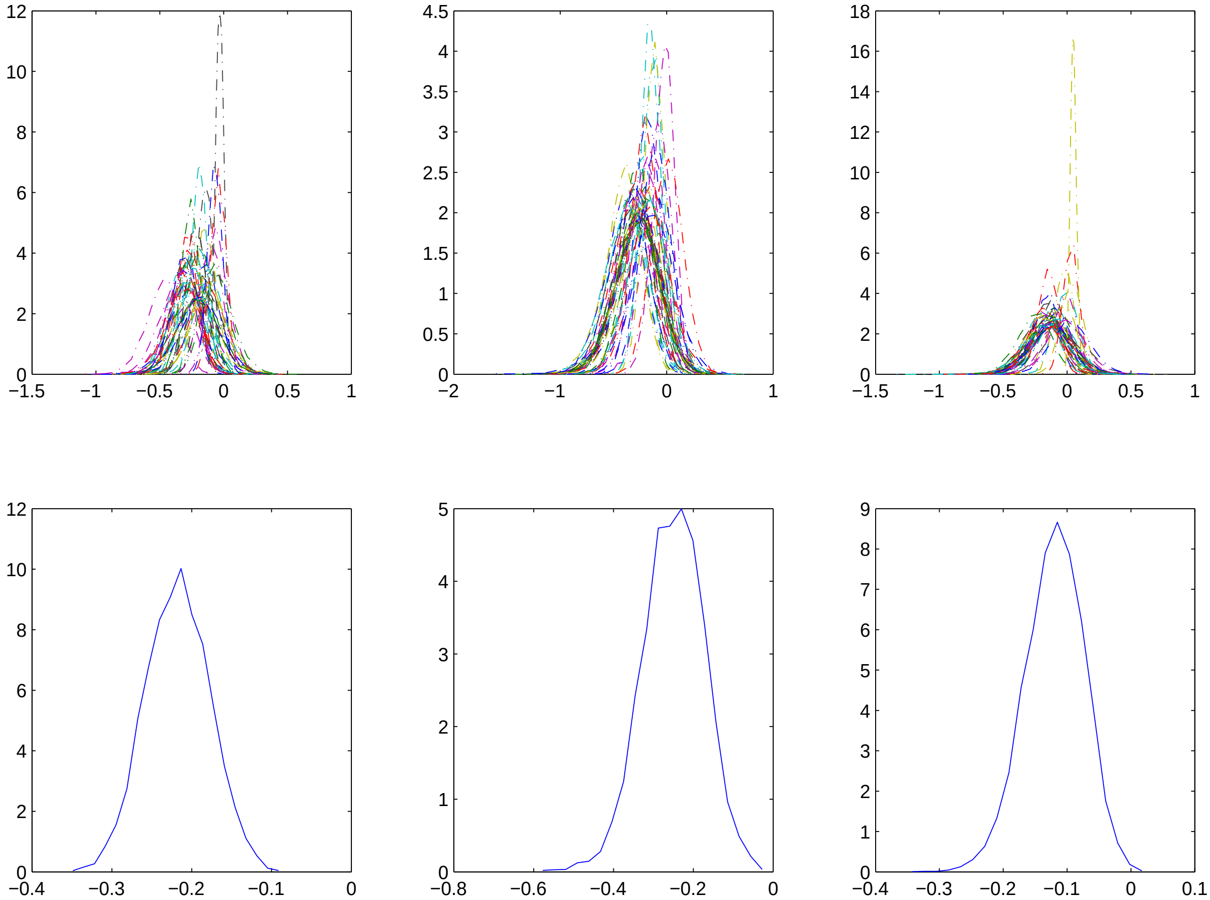
probit	I	II	III	IV
pooled	-381.3095	-308.7889	-295.4025	-244.0496
serial	-357.0324	-307.3159	-262.4228	-244.2613
heterogeneity	-352.6263	-300.7738	-258.3797	-229.1459
serial & heterogeneity	-291.6727	-268.2328	-203.1616	-198.9042
treatment	I	II	III	IV
pooled	-3280.0	-3207.6	-3199.2	-3146.8
serial	-3277.2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

Table 11: 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	$\sum$
hetergeneity	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.

Figure 1: Heterogeneity within the Probit Coefficients



Notes: Heterogeneity for reversal scheme I: left - histograms of the sampled country specific coefficient for variable mean CAD; middle - histograms of the sampled country specific coefficient for variable reserves - 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.