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Working Paper

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Economics Working Paper, No. 2009-04

Provided in Cooperation with:
Christian-Albrechts-University of Kiel, Department of Economics

Christian-Albrechts-Universität zu Kiel

Department of Economics

Economics Working Paper
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determinants and dynamics of current account reversals: an empirical analysis

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Determinants and Dynamics of Current Account Reversals: An Empirical Analysis*

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March 2, 2009

Abstract

We use panel probit models with unobserved heterogeneity, state-dependence and serially correlated errors in order to analyze the determinants and the dynamics of current-account reversals for a panel of developing and emerging countries. The likelihood-based inference of these models requires high-dimensional integration for which we use Efficient Importance Sampling (EIS). Our results suggest that current account balance, terms of trades, foreign reserves and concessional debt are important determinants of current-account reversal. Furthermore, we find strong evidence for serial dependence in the occurrence of reversals. While the likelihood criterion suggest that state-dependence and serially correlated errors are essentially observationally equivalent, measures of predictive performance provide support for the hypothesis that the serial dependence is mainly due to serially correlated country-specific shocks related to local political or macroeconomic events.

JEL classification: C15; C23; C25; F32
Keywords: Panel data, Dynamic discrete choice, Importance Sampling, Monte Carlo integration, State dependence, Spillover effects.

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*A former version of this paper circulated under the title "Dynamic Panel Probit Models for Current Account Reversals and their Efficient Estimation".

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1 Introduction

The determinants of current account reversals and their consequences for countries' economic performance have received a lot of attention following the currency crises of the 1990s. They have found renewed interest because of the huge US current account deficit in recent years. The importance of the current account comes from its interpretation as a restriction on countries' expenditure capabilities. Expenditure restrictions, generated by sudden stops and/or currency crises, can generate current account reversals, worsen an economic crises or even trigger one (see, e.g., Milesi-Ferretti and Razin, 1996, 1998, 2000, and Obstfeld and Rogoff, 2004). Typical issues addressed in the recent literature are: The extent to which current account reversals affect economic growth (Milesi-Ferretti and Razin, 2000, and Edwards, 2004a,b); The sustainability of large current account deficits for significant periods of time (Milesi-Ferretti and Razin, 2000); and possible causes for current account reversals (Milesi-Ferretti and Razin, 1998, and Edwards, 2004a,b). Our paper proposes to analyze the latter issue in the context of dynamic panel probit models, paying special attention to the potential serial dependence inherent to the occurrence of current account reversals.

Milesi-Ferretti and Razin (1998) and Edwards (2004a,b) use panel probit models with time and country specific dummies in order to investigate the determinants of current account reversals. While Milesi-Ferretti and Razin analyze a panel of low- and middle-income countries, Edwards also includes industrialized countries. These studies focus on tests of theoretical predictions relative to the causes of current account reversals, which are mainly motivated by the need to ensure that a country remains solvent. They paid less attention to potential intertemporal linkages among current account reversals and the duration of reversal processes.

However, there are several reasons to expect serial persistence in current account reversals. For example, a full current account adjustment from a non-sustainable towards a sustainable level might take several periods since responses of international trade flows are characterized by a fairly high degree of inertia (see, e.g., Junz and Rhomberg, 1973). Furthermore, past current account reversals might change the constraints and conditions relevant to the occurrence of another reversal in the future, as argued, e.g., by Falcetti and Tudela (2006) within the context of a panel analysis of currency crisis. Both scenarios would lead to *state dependence* (lagged dependent variable), whereby a country's propensity to experience a reversal depends on wether or not it experienced a reversal in the past (see, e.g., Heckman 1981). Following Falcetti and Tudela (2006), additional potential sources of serial dependence are unobserved time-invariant heterogeneity (random country specific effects) reflecting differences in institutional, political or economic factors across countries, as well as unobserved transitory differences (serially correlated country-specific errors) which might be the result of omitted serially correlated macroeconomic factors or serially correlated country-specific shocks[1].

However, unobserved and serially correlated transitory effects might be also common to all countries (serially correlated time-specific effects). As such they might reflect global shocks like oil and other commodity price shocks or, as we shall argue below, contagion effects. In particular, following the financial turbulences of the 1990s, it is recognized that spillover effects are important, especially for emerging economies. Common causes of contagion include transmission of local shocks such as currency crises through trade links, competitive devaluations, and financial links (see, e.g., Dornbusch et al., 2000).

In the present paper, we analyze the determinants and dynamics of current account reversals for a panel of developing and emerging countries considering alternative sources of persistence. Our starting point consists of a panel probit model with state dependence and random country specific effects (Section 4.1). Next, we analyze the robustness of this model against the introduction of correlated idiosyncratic error components (Section 4.2) or serially correlated common time effects (Section 4.3). We pay special attention to the predictive performance of these alternative specifications relative to the timing and the duration of reversal episodes.

Likelihood evaluation of panel probit models with unobserved heterogeneity and dynamic error components is complicated by the fact that the computation of the choice probabilities requires high-dimensional interdependent integrations. The dimension of such integrals is typically given by the number of time periods (T), or if one allows for interaction between country specific and time random ef-

[1]The notion that serial dependence could be due to unobserved permanent differences as well as transitory differences was already addressed by Keane (1993) within a model of labor supply. Keane was one of the first to estimate a panel probit model including both sources of serial dependence.

fects by $T+N$, where N is the number of countries. Efficient likelihood estimation of such models generally relies upon Monte-Carlo (MC) integration techniques (see, e.g., Geweke and Keane, 2001 and the references therein). Here we use the Efficient Importance Sampling (EIS) MC methodology developed by Richard and Zhang (2007), which represents a powerful and generic high dimensional simulation technique. It relies on simple auxiliary Least-Squares regressions designed to maximize the numerical accuracy of the likelihood integral approximations. As illustrated in Liesenfeld and Richard (2008a,b), EIS is particularly well suited to handle unobserved heterogeneity and serially correlated errors in panel models for binary and multinomial variables. In particular, as shown in Liesenfeld and Richard (2008b), EIS substantially improves the numerical efficiency of the GHK procedure of Geweke (1991), Hajivassiliou (1990), and Keane (1994), which represents the most popular MC procedure used for the evaluation of choice probabilities under dynamic panel probit models – see, e.g., Hyslop (1999), Greene (2004), and Falcetti and Tudela (2006).

In conclusion of our introduction, we note that there are a number of other studies which empirically analyze discrete events (macroeconomic and/or financial crises) using non-linear panel models. See, e.g., Calvo et al. (2004) on sudden stops or Eichengreen et al. (1995) and Frankel and Rose (1996) on currency crises. The study most closely related to our paper with respect to the empirical methodology is that of Falcetti and Tudela (2006), who analyze the determinants of currency crises using a dynamic panel probit model accounting for different sources of intertemporal linkages. However, contrary to our study, they do not consider specifications capturing possible spillover effects of crises and their estimation strategy is based on the standard GHK procedure.

The remainder of this paper is organized as follows. In the next section we discuss possible determinants of current account reversals and reasons to expect serial persistence in reversals. In Section 3 we describe the data set and introduce the technical definition of current account reversal used in our analysis. Section 4 presents the dynamic panel probit models used to analyze current account reversals. ML-estimation results are discussed in Section 5. Predictive performances are compared in Section 6 and conclusions are drawn in Section 7. Details of the EIS implementation for the models under consideration are regrouped in an Appendix.

2 Determinants and Dynamics of Current Account Reversals

2.1 Determinants

Milesi-Feretti and Razin (1998) argue that the most obvious reason for a country to experience a current account reversal is the need to ensure solvency, which they relate to the stabilization of the ratio of external liabilities to GDP. Let tb^* denote the trade balance needed to ensure the stabilization of this ratio and tb the trade balance before the reversal. Then, abstracting from equity and foreign direct investment flows and stocks, the reversal needed to ensure solvency can be according to Milesi-Feretti and Razin (1998) written as

$$\begin{aligned} REV &= tb^* - tb = (rint^* - app^* - gr^*) \cdot d - tb \\ &= [(rint^* - rint) - app^* - gr^*] \cdot d - (s - i), \end{aligned} \tag{1}$$

where $rint$ is the real interest rate on external debt, gr is the growth rate of the economy, app is the rate of real appreciation, d is the ratio of external debt to GDP, and s and i are the shares of domestic savings and investment to GDP. The variables indexed by a star denote the post-reversal level and those without a star the pre-reversal level.

This simple framework points to several determinants for the occurrence of large reductions in the current-account imbalance. The size of the reversal needed to ensure solvency grows with the initial trade imbalance. Given the initial trade imbalance, the size of the required reversal is increasing in the level of external liabilities as well as in the rate of interest on external debt, while it is decreasing in the growth rate. Note also that an increase in the world interest rate lowers the interest rate differential, increasing the required reversal size. In fact, any change in $rint^*$ and gr^* will affect a country's intertemporal budget constraint and its current-account imbalance.

Further potential determinants for current account reversals are obtained from models developed to analyze the ability of a country to sustain a large current account deficit for significant periods of time – see, e.g., Milesi-Feretti and Razin (1996). They indicate that the sustainability of an external imbalance and, therefore, the probability of its reduction depend on factors such as a country's degree of openness, its international reserves, its terms of trade and fiscal environment.

While the solvency condition characterized by Equation (1) helps identifying potential causes for the occurrence of current account reversals, it is static and, therefore, not helpful to discuss the dynamics of reversals. However, as discussed further below, there are several reasons to expect serial dependence in the occurrence of large reductions of current account deficits. Within a panel probit model for the analysis of the determinants of reversals they imply state dependence and/or serially correlated error terms.

2.2 State dependence

Assuming that the domestic economy grows at a rate below the real interest rate (adjusted by the rate of real appreciation), the solvency condition (1) requires a trade surplus. This surplus is often obtained by currency devaluations. However, while changes in exchange rate can be abrupt, subsequent changes in trade can be much slower. See, e.g., Junz and Rhomberg (1973) who analyze the response of international trade flows to changes in the exchange rate, and conclude that the effects of price changes on trade flows usually stretch out over more than three years. In particular, they argue that agents react with lags and identify the following sources for delayed responses: a recognition lag, which is the time it takes for economic agents to become aware of changes in the competitive environment; a decision lag, which lasts from the moment in which the new situation has been recognized to the one in which an action is undertaken (producers need to be convinced that the new opportunities are long lasting and profitable enough to compensate for adjustment costs); and finally, mostly technical lags in production, delivery and substitution of materials and equipments in response to relative price changes.

In line with these arguments, Himarios (1989) finds that nominal devaluations result in significant real devaluations that last for at least three years, and that real devaluations induce significant trade flows that are distributed over a two- to three-year period. Therefore, the full current account adjustment implied by Equation (1) might take longer than one year, leading to a state dependence for yearly data such as those used below. In order to account for the possibility that a reversal process stretches over more than a year after it is triggered, we include the lagged dependent variable among the regressors of our panel-probit specifications.

2.3 Serially correlated error terms

Further potential sources of serial dependence in the occurrence of large reductions in the current account imbalance are differences in the propensity to experience large reductions across countries. Such heterogeneity might be due to time-invariant differences in institutional, political or economic factors which can not be controlled for. In order to take these differences into account, we use a random effect approach with a country-specific time-invariant error component, which induces a cross-period correlation of the overall error terms. An alternative approach to capture time-invariant differences would be to use a model with fixed effect based upon country-specific dummy variables, such as the one used in the studies of Milesi-Ferretti and Razin (1998) and Edwards (2004a,b). However, such a model requires the estimation of a large number of parameters, leading to a significant loss of degrees freedom. Furthermore, the ML-estimator does not exist as soon as the dependent variable does not vary (as shown in Table 1, our data set includes countries that never experienced a reversal).

Unobserved differences in the propensity to experience large reductions in the current account deficit could also be serially correlated, rather than time-invariant. As such they might reflect serially correlated shocks associated with regional conflicts, uncertainty about government transition and political changes, as well as regional commodity price shocks affecting the probability of experiencing current account reversals. In order to take those effects into account, we assume an AR(1) specification for the country specific transitory error component.

Finally, unobserved and serially correlated transitory effects might also be common to all countries reflecting either contagion effects or global shocks such as oil or commodity price shocks. The former have received a lot of attention following the currency crises of the 1990s which rapidly spread across emerging countries (see, e.g., Edwards and Rigobon, 2002). A crisis in one country may lead investors to withdraw their investments from other markets without taking into account differences in economic fundamentals. In addition, a crisis in one economy can also affect the fundamentals of other countries through trade links and currency devaluations. Trading partners of a country in which a financial crisis has induced a sharp currency depreciation could experience a deterioration of the trade balance and current account resulting from a decline in exports and an increase in imports (see Corsetti et al., 1999). In the words of the former Managing Director of the IMF: "from the viewpoint of the international system, the devaluations in Asia will lead to large current account surpluses in those countries, damaging the competitive position of other countries and requiring them to run current account deficit." Fisher (1998).

Currency devaluations of countries that experience a crisis can often be seen as a *beggar-thy-neighbor* policy in the sense that they incite output growth and employment domestically at the expense of output growth, employment and current account deficit abroad (Corsetti et al., 1999). *Competitive devaluations* also happen in response to this process, as other economies may in turn try to avoid competitiveness loss through devaluations of their own currency. This appears to have happened during the East Asian crises in 1997 (Dornbusch et al., 2000).

If data are collected at short enough time intervals (monthly or quarterly observations), such spill-over effects would become manifest in the dependence of a country's propensity to experience a reversal from lagged reversals by other countries. However, with yearly data the time intervals are presumably not fine enough to observe such short-run spill-over effects of one country on another and contagion would more likely translate into a common time effect. Hence, we use an AR(1) time-random effect which is common to all countries in order to account for contagion effects together with global shocks.

3 The Data

Our data set consists of an unbalanced panel for 60 low and middle income countries from Africa, Asia, and Latin America and the Caribbean. The complete list of countries is given on Table 1. The time span of the data set ranges from 1975 to 2004, although the unavailability of some explanatory variables often restrict the analysis to shorter time intervals. The minimum number of periods for a country is 9, the maximum is 18 and the average is 16.5 for a total of 963 yearly observations. The initial values of the binary dependent variable indicating the occurrence of a current account crisis are known for the initial time period $t = 0$ for all countries. The sources of the data are the World Bank's World

Development Indicators (2005) and the Global Development Finance (2004).

Current account reversals are defined as in Milesi-Ferretti and Razin (1998). According to this definition a current account reversal has to meet three requirements. The first is an average reduction of the current account deficit of at least 3 percentage points of GDP over a period of 3 years relative to the 3-year average before the event. The second requirement is that the maximum deficit after the reversal must be no larger than the minimum deficit in the 3 years preceding the reversal. The last requirement is that the average current account deficit over the 3-year period starting with the event must be less than 10% of GDP. According to this definition we find current account reversals for 100 individual periods in 44 countries (10% of the total number of observations). Defining the duration of a reversal episode as the number of consecutive periods with a reversal we observe 66 episodes with an average duration of 1.52 years and a maximal duration of 4 years (see Figure 3 below for a plot of the relative frequencies of the durations).

As discussed in Section 2.1, the selection of the explanatory variables follows mainly the study of Milesi-Ferretti and Razin (1998). We include lagged macroeconomic, external, debt and foreign variables. The macroeconomic variables are the annual growth rate of GDP (AVGGROW), the share of investment to GDP proxied by the ratio of gross capital formation to GDP (AVGINV), government expenditure (GOV) and interest payments relative to GDP (INTPAY). The external variables are the current account balance as a fraction of GDP (AVGCA), a terms of trade index set equal to 100 for the year 2000 (AVGTT), the share of exports and imports of goods and services to GDP as a measure of trade openness (OPEN), the rate of official transfers to GDP (OT) and the share of foreign exchange reserves to imports (RES). The debt variable we include is the share of consessional debt to total debt (CONCDEB). Foreign variables such as the US real interest rate (USINT) and the real growth rates of the OECD countries (GROWOECD) are also included to reflect the influence of the world economy. As in Milesi-Ferretti and Razin (1998), the current account, growth, investment and terms of trade variables are 3-years averages, in order to ensure consistency with the way reversals are measured.

4 Empirical Specifications

Our baseline specification consists of a dynamic panel probit model of the form

$$y_{it}^* = x_{it}'\pi + \kappa y_{it-1} + e_{it}, \quad y_{it} = \mathbb{I}(y_{it}^* > 0), \quad i = 1, ..., N, \quad t = 1, ..., T, \qquad (2)$$

where $\mathbb{I}(y_{it}^* > 0)$ is an indicator function that transforms the latent continuous variable y_{it}^* for country i in year t into the binary variable y_{it}, indicating the occurrence of a current account reversal ($y_{it} = 1$). The error term e_{it} is assumed to be normally distributed with zero mean and a fixed variance. Since Equation (2) is only identified up to a positive multiplicative constant, a normalization condition will be required for each model variant (see Section 4.4 below). The vector x_{it} contains the observed macroeconomic, external, debt and foreign variables which might affect the incidence of a reversal. The lagged dependent variable on the right hand side captures possible state dependence. It implies that the covariates in x_{it} have not only a contemporaneous but also a persistent effect on the probability of a reversal.

The most restrictive version of the panel probit assumes that the error e_{it} is independent across time and countries and imposes the restriction $\kappa = 0$. This produces the standard pooled probit estimator which ignores possible serial dependence and unobserved heterogeneity which cannot be attributed to the variables in x_{it}.

4.1 Random country-specific effects

In order to account for unobserved time invariant heterogeneity across countries we consider the random effect model proposed by Butler and Moffitt (1982). It assumes the following specification for the error term in Equation (2):

$$e_{it} = \tau_i + \epsilon_{it}, \qquad \epsilon_{it} \sim \text{i.i.d.N}(0, 1), \qquad \tau_i \sim \text{i.i.d.N}(0, \sigma_\tau^2). \qquad (3)$$

The country-specific term τ_i captures potential permanent latent differences in the propensity to experience a reversal. It is assumed that τ_i and ϵ_{it} are independent from the variables included in x_{it}. If, however, x_{it} did contain variables reflecting countries' general susceptibility to current account crises, then τ_i would be correlated with x_{it}. We also assume that the observed initial states y_{i0} are non-random constants. This assumption eliminates an 'initial condition problem' due to correlation between τ_i and y_{i0} (see, e.g., Wooldridge, 2005). Since, however, ignoring correlation between τ_i and x_{it} and y_{i0} would lead to inconsistent estimates, we shall test below for such correlation.

Finally, note that the time-invariant heterogeneity component τ_i implies a constant cross-period correlation of the error term e_{it} which is given by $\mathrm{corr}(e_{it}, e_{is}) = \sigma_\tau^2/(\sigma_\tau^2 + 1)$ for $t \neq s$ (see, e.g., Greene, 2003).

The Butler-Moffitt model (2) and (3) can be estimated by ML. Let $\underline{y} = \{\{y_{it}\}_{t=1}^T\}_{i=1}^N$, $\underline{x} = \{\{x_{it}\}_{t=1}^T\}_{i=1}^N$ and θ denote the parameter vector to be estimated. The likelihood function is given by $L(\theta; \underline{y}, \underline{x}) = \prod_{i=1}^N I_i(\theta)$, where I_i represents the likelihood contribution of country i. The latter has the form

$$I_i(\theta) = \int_{\mathbb{R}^1} \prod_{t=1}^T \left[\Phi_{it}^{y_{it}} (1 - \Phi_{it})^{(1-y_{it})}\right] f_\tau(\tau_i) d\tau_i, \tag{4}$$

where $\Phi_{it} = \Phi(x_{it}'\pi + \kappa y_{it-1} + \tau_i)$, Φ denotes the cdf of the standardized normal distribution and f_τ the pdf of τ_i. In the application below, the one dimensional integrals in τ_i are evaluated using a Gauss-Hermite quadrature rule (see, e.g., Butler and Moffitt, 1982).

Once the parameters have been estimated, the Gauss-Hermite procedure can also be used to compute estimates of the random country-specific effects τ_i or of functions thereof. Those estimates are instrumental for computing predicted probabilities and average partial effects as well as for validating the orthogonality conditions imposed on τ_i. Let $g(\tau_i)$ denote a function of τ_i. Its conditional expectation given the complete sample information $(\underline{y}, \underline{x})$ obtains as

$$\mathrm{E}[g(\tau_i)|\underline{y}, \underline{x}; \theta] = \frac{\int_{\mathbb{R}^1} g(\tau_i) h(\underline{y}_i, \tau_i|\underline{x}_i; \theta) d\tau_i}{\int_{\mathbb{R}^1} h(\underline{y}_i, \tau_i|\underline{x}_i; \theta) d\tau_i}, \tag{5}$$

where h denotes the joint conditional pdf of $\underline{y}_i = \{y_{it}\}_{t=1}^T$ and τ_i given $\underline{x}_i = \{x_{it}\}_{t=1}^T$, as defined by the integrand of the likelihood (4). For the evaluation of the numerator and denominator by Gauss-Hermite, the parameters θ are set to their ML-estimates.

Estimates $\hat{\tau}_i$ of the random effects obtain by setting $g(\tau_i) = \tau_i$ in Equation (5). An auxiliary regression of those estimates against the time average of the explanatory variables and the initial conditions provides a direct test of the validity of the orthogonality condition between τ_i and $(\underline{x}_i, y_{i0})$.

Next, in order to obtain predicted probabilities and average marginal effects we consider the conditional response probability

$$p(y_{it} = 1|x_{it}, y_{it-1}, \tau_i) = \Phi(x_{it}'\pi + \kappa y_{it-1} + \tau_i), \tag{6}$$

and its partial derivative w.r.t. the kth (continuous) variable in x_{it}

$$\partial_{x_{itk}} p(y_{it} = 1|x_{it}, y_{it-1}, \tau_i) = \pi_k \phi(x_{it}'\pi + \kappa y_{it-1} + \tau_i), \tag{7}$$

where ϕ denotes the standardized Normal density and π_k the regression coefficient of the covariate x_{itk}. Both expressions represent functions of τ_i, which can be averaged across the conditional distribution of τ_i given the sample information $(\underline{y}, \underline{x})$, according to Equation (5). The average marginal effect of the kth covariate then obtains as the sample mean across i and t of the averaged partial derivatives (7). Analogously, we compute the average partial effect of the binary lagged dependent variable as the sample mean of the differences in the probabilities $p(y_{it} = 1|x_{it}, y_{it-1} = 1, \tau_i)$ and $p(y_{it} = 1|x_{it}, y_{it-1} = 0, \tau_i)$ averaged across the conditional distribution of τ_i given $(\underline{y}, \underline{x})$.

4.2 Serially correlated country-specific errors

We generalize the random effect specification introduced in Section 4.1 by assuming that ϵ_{it} in Equation (3) follows an idiosyncratic AR(1) process, capturing persistent country-specific shocks and omitted macroeconomic or political factors. Accordingly, Equation (3) is generalized into

$$e_{it} = \tau_i + \epsilon_{it}, \qquad \epsilon_{it} = \rho\epsilon_{it-1} + \eta_{it}, \qquad \eta_{it} \sim \text{i.i.d.N}(0, 1), \tag{8}$$

where τ_i and η_{it} are mutually independent. As before, they are also assumed to be independent from the variables included in x_{it} and y_{i0}. In order to ensure stationarity we assume that $|\rho| < 1$.

The computation of the likelihood contribution $I_i(\theta)$ for model (3) and (8) now requires the evaluation of $(T + 1)$-dimensional integrals. Let $\underline{\lambda}_{it}' = (\epsilon_{it}, \epsilon_{it-1}, \tau_i)$, $\underline{\lambda}_{i1}' = (\epsilon_{i1}, \tau_i)$, and $\underline{\lambda}_i' = (\tau_i, \epsilon_{i1}, ..., \epsilon_{iT})$. Under the assumption that $\epsilon_{i0} = 0$, the likelihood contribution of a country is given by

$$I_i(\theta) = \int_{\mathbb{R}^{T+1}} \left[\prod_{t=1}^{T} \varphi_t(\underline{\lambda}_{it}) \right] f_\tau(\tau_i) d\underline{\lambda}_i, \tag{9}$$

with

$$\varphi_t(\underline{\lambda}_{it}) = \begin{cases} \mathbb{I}(\epsilon_{it} \in D_{it})\phi(\epsilon_{it} - \rho\epsilon_{it-1}), & \text{if} \quad t > 1 \\ \mathbb{I}(\epsilon_{i1} \in D_{i1})\phi(\epsilon_{i1}), & \text{if} \quad t = 1, \end{cases} \tag{10}$$

$$D_{it} = \begin{cases} [-(\mu_{it} + \tau_i) \ , \ \infty), & \text{if} \quad y_{it} = 1 \\ (-\infty \ , \ -(\mu_{it} + \tau_i)], & \text{if} \quad y_{it} = 0, \end{cases} \tag{11}$$

where $\mu_{it} = x_{it}'\pi + \kappa y_{it-1}$.

In order to evaluate the (truncated) Gaussian integral $I_i(\theta)$ MC-integration techniques can be used. The most popular MC approach for such integrals is the GHK procedure of Geweke (1991), Hajivassiliou (1990), and Keane (1994), belonging to the class of Importance Sampling techniques. However, as shown by Lee (1997) and Geweke et al. (1997), GHK likelihood evaluation based upon commonly used simulation sample sizes can produce severely biased ML estimates, especially, when serial correlation in the errors is strong and/or T is large. Hence, we use instead the EIS procedure developed by Richard and Zhang (2007). As shown in Liesenfeld and Richard (2008b), EIS covers the GHK procedure as a special case and significantly improves the numerical accuracy of GHK. A description of the particular EIS implementation used for the likelihood (9) is provided in the Appendix[2].

As in Section 4.1, we compute probability predictions and average marginal effects from the corresponding response probability

$$p(y_{it} = 1 | x_{it}, y_{it-1}, \tau_i, \epsilon_{it-1}) = \Phi(x_{it}'\pi + \kappa y_{it-1} + \tau_i + \rho\epsilon_{it-1}), \tag{12}$$

[2]Liesenfeld and Richard (2008b) consider the EIS likelihood evaluation for multiperiod multinomial probit models with serially correlated errors but without unobserved random effects (τ). If we rewrote the likelihood in Equation (9) in terms of a T-dimensional integral in the *composite* errors $(e_1, \ldots, e_T)'$ (which follow according to Equation (8) a multivariate Gaussian distribution), we could directly apply the EIS implementation of Liesenfeld and Richard (2008b) to the present binomial model. However, such an implementation would not directly deliver MC estimates of the conditional expectation of the random effect τ, which we use to test the orthogonality conditions. Hence, we implement EIS for the $(T+1)$-dimensional integral (9) in $(\epsilon_1, ..., \epsilon_T, \tau)$. See the Appendix for details.

together with its partial derivatives w.r.t. the covariates, all of which are functions of the latent variables τ_i and ϵ_{it-1}. The EIS procedure for the likelihood evaluation delivers as a by-product accurate MC-approximations of the conditional expectation of these functions given the sample information, which obtain as

$$\mathrm{E}[g(\tau_i, \epsilon_{it-1})|\underline{y}, \underline{x}; \theta] = \frac{\int_{\mathbb{R}^{T+1}} g(\tau_i, \epsilon_{it-1})\ h(\underline{y}_i, \underline{\lambda}_i|\underline{x}_i; \theta) d\underline{\lambda}_i}{\int_{\mathbb{R}^{T+1}} h(\underline{y}_i, \underline{\lambda}_i|\underline{x}_i; \theta) d\underline{\lambda}_i}. \tag{13}$$

Here $h(\underline{y}_i, \underline{\lambda}_i|\underline{x}_i; \theta)$ denotes the joint conditional distribution of $\underline{y}_i$ and $\underline{\lambda}_i$ given $\underline{x}_i$ as given by the integrand of the likelihood (9).

4.3 Serially correlated time-specific effects

Since the panel models introduced above ignore correlation across countries, they do not account for potential spill-over effects and global shocks common to all countries. In order to address this issue we consider next the following factor specification for the error e_{it} in the probit regression (2):

$$e_{it} = \tau_i + \xi_t + \epsilon_{it}, \qquad \epsilon_{it} \sim \text{i.i.d.N}(0, 1), \qquad \tau_i \sim \text{i.i.d.N}(0, \sigma_\tau^2), \tag{14}$$

with

$$\xi_t = \delta\xi_{t-1} + \nu_t, \qquad \nu_t \sim \text{i.i.d.N}(0, \sigma_\xi^2), \tag{15}$$

where τ_i, ϵ_{it} and ν_t are mutually independent and independent from x_{it} and y_{i0}. It is assumed that $|\delta| < 1$. The common dynamic factor ξ_t represents unobserved time-specific effects which induce correlation across countries, resulting from spillover effects and common shocks. This is the same factor specification as that used in Liesenfeld and Richard (2008a) for a microeconometric application. It is similar to the linear panel factor model discussed, e.g., by Baltagi (2005) and primarily used for the analysis of macroeconomic data.

The likelihood function for the random effect panel model consisting of Equations (2), (14), and (15) is given by

$$L(\theta; \underline{y}, \underline{x}) = \int_{\mathbb{R}^{T+N}} \left[\prod_{i=1}^{N}\prod_{t=1}^{T}[\Phi(z_{it})]^{y_{it}}[1 - \Phi(z_{it})]^{(1-y_{it})}\right] p(\underline{\tau}, \underline{\xi}) d\underline{\tau}, d\underline{\xi}, \tag{16}$$

where $\underline{\xi} = \{\xi_t\}_{t=1}^{T}$, $\underline{\tau} = \{\tau_i\}_{i=1}^{N}$, $z_{it} = x'_{it}\pi + \kappa y_{it-1} + \tau_i + \xi_t$, and $p(\underline{\tau}, \underline{\xi})$ denotes the joint density of $\underline{\tau}$ and $\underline{\xi}$.

Note that the presence of a time effect ξ_t common to all countries prevents us from factorizing the likelihood function into a product of integrals for each individual country as above. However, we can still use the EIS technique for the evaluation of the likelihood function (16). See Richard and Zhang (2007) and Liesenfeld and Richard (2008a) for a detailed description of the EIS implementation for this likelihood function[3].

Estimates for functions of the unobserved random effects are obtained as above. In particular, the conditional expectation of such functions given the sample information has the form

$$\mathrm{E}[g(\tau_i, \xi_t)|\underline{y}, \underline{x}; \theta] = \frac{\int_{\mathbb{R}^{N+T}} g(\tau_i, \xi_t)\ h(\underline{y}, \underline{\tau}, \underline{\xi}|\underline{x}; \theta) d\underline{\xi} d\underline{\tau}}{\int_{\mathbb{R}^{N+T}} h(\underline{y}, \underline{\tau}, \underline{\xi}|\underline{x}; \theta) d\underline{\xi} d\underline{\tau}}, \tag{17}$$

where h denotes the joint conditional pdf of $\underline{y}$, $\underline{\xi}$ and $\underline{\tau}$ given $\underline{x}$, as given by the integrand of the likelihood function (16). As before, we can construct probability predictions and average marginal effects from the conditional response probability

$$p(y_{it} = 1|x_{it}, y_{it-1}, \tau_i, \xi_t) = \Phi(x'_{it}\pi + \kappa y_{it-1} + \tau_i + \xi_t), \tag{18}$$

and its partial derivatives w.r.t. the covariates.

4.4 A note on normalization

In Equations (3), (8), (14), (15) we followed the standard practice of normalizing the probit equation (2) by setting the variance of the residual innovations ϵ_{it} equal to 1. It follows that the variances of the composite error term e_{it} differ across models, implying corresponding differences in the implicit normalization

[3] In contrast to the panel probit model (2), (14), and (15) assumed here, Richard and Zhang (2007) and Liesenfeld and Richard (2008a) consider a similar panel logit specification where the error component ϵ_{it} in Equation (14) follows a logistic distribution. However, this difference requires only a minor adjustment in the EIS implementation, whereby logistic cdfs are replaced by probit cdfs.

rule. The variances of e_{it} under the different specifications are given by

$$\begin{aligned} \text{Equation (3)} &: \quad \sigma_e^2 = 1 + \sigma_\tau^2 \\ \text{Equation (8)} &: \quad \sigma_e^2 = \frac{1}{1-\rho^2} + \sigma_\tau^2 \\ \text{Equations (14)+(15)} &: \quad \sigma_e^2 = 1 + \sigma_\tau^2 + \frac{\sigma_\xi^2}{1-\delta^2}. \end{aligned}$$

Predicted probabilities and estimated average marginal effects are invariant with respect to the normalization rule. The estimated coefficients are not as they are proportional to σ_e. We produce estimates of σ_e in order to facilitate comparisons between estimated coefficients across models.

5 Empirical Results

5.1 Model 1: Pooled probit

Table 2 provides the ML estimates for the pooled probit model given by Equation (2) (model 1) together with the corresponding estimated partial effects of the explanatory variables on the probability of a current account reversal. The results for the static model ($\kappa = 0$) are reported in the left columns and those of the dynamic specification ($\kappa \neq 0$) in the right columns.

The parameter estimates for the covariates in x_{it} are all in line with the results in the empirical literature on current account crises (see Milesi-Ferretti and Razin, 1998, and Edwards 2004a,b) and confirm the theoretical solvency and sustainability considerations. Sharp reductions of the current-account deficit are more likely in countries with a high current account deficits (AVGCA) and with higher government expenditures (GOV). The significant effect of the current account deficit level is consistent with a need for sharp corrections in the trade balance to ensure that the country remains solvent. Interpreting current account as a constraint on expenditures, the positive impact of government expenditure on the reversal probability can be attributed to fact that an increase of government expenditures leads to a deterioration of the current account. However, the inclusion of the lagged dependent variable reduces this effect and renders it non significant. This suggests that government expenditures might capture some form of omitted serial dependence under the static specification. The marginal effect of foreign reserve (RES) is negative and significant which suggests that low levels of reserves make it more difficult to sustain a large trade imbalance and may also reduce foreign investors' willingness to lend (Milesi-Ferretti and Razin, 1998). Also, reversals seem to be less common in countries with a high share of concessional debt (CONCDEB). This would be consistent with the fact that concessional debts tend to be higher in countries which have difficulties reducing external imbalances. Finally, countries with a lower degree of openness (OPEN), weaker terms of trade (AVGTT) and higher GDP growth (AVGGROW) seem to face higher probabilities of reversals, especially when growth rate in OECD countries (GROWOECD) and/or US interest rate (USINT) are higher – though none of these five coefficients are statistically significant.

Note that the size of the estimated marginal effects for the significant economic covariates on the probability of reversals are typically fairly small, ranging from 0.004 to 0.026. Nevertheless, they are far from being negligible when applied to the low unconditional probability of experiencing a reversal which is approximately 0.1.

The inclusion of the lagged current account reversal variable substantially improves the fit of the model as indicated by the significant increase of the maximized log-likelihood value. The estimated coefficient κ measuring the impact of the lagged dependent state variable is positive and significant at the 1% significance level with a large estimated partial effect of 0.21. This suggests that a current account reversal significantly increases the probability of a further reversal the following year. This would be consistent with the hypothesis that reversal processes stretch over more than a year due to slow adjustments in international trade flows (see, Junz and Rhomberg, 1973, and Himaraios, 1989).

In order to analyze the dynamic effects of a covariate x_{itk} implied by the model with lagged dependent variable we use the sample average of the l-step ahead marginal effect, i.e.,

$$\frac{1}{N(T-\ell)} \sum_{i=1}^{N} \sum_{t=1}^{T-\ell} \partial_{x_{itk}} p(y_{it+\ell} = 1 | x_{it+\ell}, ..., x_{it}, y_{it-1}), \qquad \ell = 1, 2, \dots \,. \tag{19}$$

The probability $p(y_{it+\ell} = 1 | x_{it+\ell}, ..., x_{it}, y_{it-1})$ is obtained by considering the event tree associated with all possible y_{it}-trajectories starting in period t and ending in period $t + \ell$ with $y_{it+\ell} = 1$. Analogously, the dynamic effects of the state variable is measured by

$$\frac{1}{N(T-\ell)} \sum_{i=1}^{N} \sum_{t=1}^{T-\ell} \Big[p(y_{it+\ell} = 1 | x_{it+\ell}, ..., x_{it+1}, y_{it} = 1) \qquad (20)$$

$$- p(y_{it+\ell} = 1 | x_{it+\ell}, ..., x_{it+1}, y_{it} = 0) \Big], \quad \ell = 1, 2, ... \, .$$

The upper left panel of Figure 1 plots the dynamic marginal effects for the significant covariates (AVGCA, RES, CONCDEB) and the lagged state variable for $\ell = 1, ..., 4$, respectively. It reveals substantial long-run effects of the state variable, whereby the occurrence of a current account reversal increases a country's propensity to experience further large reductions in the current account in subsequent years. This effect appears to stretch over a two-to-three-year period. This would be in line with the result of Himarios (1989) showing that changes in trade flows triggered by currency devaluations often used to correct the trade balance are distributed over a time span of a about two or three years. However, note that this long-run state dependence does not translate into significant long-run effects of the covariates AVGCA, RES, and CONCDEB which is consistent with the fact that their contemporaneous effects reported in Table 2 are already fairly small.

5.2 Model 2: Random country-specific effects

Table 3 reports the estimates of the dynamic Butler-Moffitt model with random country specific effects as specified by Equations (2) and (3) (model 2). The ML-estimates are obtained using a 20-points Gauss-Hermite quadrature. The estimate of the coefficient σ_τ indicates that only 3% of the total variation in the latent error is due to unobserved country-specific heterogeneity and this effect is not statistically significant. Nevertheless, the maximized log-likelihood of the random effect model is significantly larger than that of the dynamic pooled probit model with a likelihood-ratio (LR) test statistic of 5.57. Since the parameter value under the Null hypothesis $\sigma_\tau = 0$ lies at the boundary of the admissible parameter space, the distribution of the LR-statistic under the Null is a $(0.5\chi^2_{(0)} + 0.5\chi^2_{(1)})$-distribution, where $\chi^2_{(0)}$ represents a degenerate distribution with all its mass at origin (see, e.g., Harvey, 1989). Whence, the critical value for a significance level of 1% is the 0.98-quantile of a $\chi^2_{(1)}$-distribution which equals 5.41. All in all, the evidence in favor of the random effect specification for time-invariant differences of institutional, political, and economic factors across countries is borderline. Actually, the marginal effects as well as the predicted dynamic effects (see, upper right panel of Figure 1) obtained under the random country-specific effect model are very similar to those for the dynamic pooled model.

In order to check the assumption that τ_i is independent of x_{it} and y_{i0} we ran the following auxiliary regression:

$$\hat{\tau}_i = \psi_0 + \bar{x}_{i\cdot}'\psi_1 + y_{i0}\psi_2 + \zeta_i, \qquad i = 1, ..., n, \tag{21}$$

where the vector $\bar{x}_{i\cdot}$ contains the mean values of the x_{it}-variables over time (except for the US interest rate and the OECD growth rate). The value of the F-statistic for the null $\psi_1 = 0$ is 1.94 with critical values of 2.71 and 2.03 for the 1% and 5% significance levels. The absolute value of the t-statistic for the null $\psi_2 = 0$ is 2.01 with critical values of 2.68 and 2.01 for the 1% and 5% levels. Whence, evidence that τ_i might be correlated with $\bar{x}_{i\cdot}$ and y_{i0} is inconclusive.

5.3 Model 3: AR(1) country-specific errors

We now turn to the ML-EIS estimates of the dynamic random effect model with AR(1) idiosyncratic errors (model 3) as specified by Equations (2) and (8). It ought to capture possible serially correlated shocks associated with regional political changes or conflicts and persistent local macroeconomic events like commodity price shocks. The ML-EIS estimation results based on a simulation sample size of $S = 100$ are given in the left columns of Table 4 [4].

The results indicate that the inclusion of a country-specific AR(1) error component has significant effects on the dynamic structure of the model but only a slight impact on the marginal effects of the x_{it}-variables, which remain typically very close to those of the pure random country-specific effect model in Table 3. An exception is the effect of the terms of trade (AVGTT) which becomes signifi-

[4] We also estimated the parameters of model 3 using the standard GHK procedure based on $S = 100$. The comparison of those estimates (not provided here) with the ML-EIS estimates provided in Table 4 reveal that the parameter estimates for the explanatory variables are generally similar for both procedures. However, the estimates of the parameters governing the the dynamics $(\kappa, \sigma_\tau, \rho)$ are noticeably different. This is fully in line with results of the MC-study of Lee (1997), indicating that the ML-GHK estimates of those parameters are often severely biased.

cant at the 10% level. Also, while the parameter σ_τ governing the time-invariant heterogeneity remains statistically insignificant, the estimated coefficient κ associated with the lagged dependent variable and its partial effect are now much smaller. This leads to a substantial attenuation of the long-run effect of the lagged state variable (see lower left panel of Figure 1). The estimate of the persistence parameter of the AR(1) error component ρ equals 0.35 and is statistically significant at the 10% level. However, the corresponding LR-statistic equals 2.40 and is not significant. Hence, despite its impact on the dynamic structure of the model, the inclusion of an AR(1) error component does not significantly improve the overall fit.

Since a lagged dependent variable and a country-specific AR(1) error component can generate similar looking patterns of persistence in the dependent variable, these results suggest that the AR(1) error captures some of the serial dependence which is captured by the lagged dependent variable under the pooled probit and the pure random country-specific effect model. However, the small likelihood improvement obtained by the inclusion of an AR(1) error together with the fairly large standard errors of the estimates for κ and ρ suggest that the model has difficulties separating these two sources of serial dependence. In order to verify this conjecture, we re-estimated the model with the AR(1) country-specific error component without state-dependence. The ML-EIS results are provided in the right columns of Table 4 and confirm our conjecture. In fact, the estimated AR coefficient ρ increases to 0.59 and is now highly significant according to both the t- and LR-test statistics, while the maximized likelihood value are not significantly different from those obtained for the models including either state-dependence only (Table 3) or both state-dependence and an AR error component (left columns of Table 4).

All in all, our results indicate that the data are ambiguous on the question of whether the observed persistence in current account reversals is due to state dependence associated with the hypothesis of slow adjustments in international trade flows or due to serially correlated country-specific shocks related to local political or macroeconomic events.

5.4 Model 4: AR(1) time-specific effects

We now turn to the estimation results of the dynamic panel model given by Equations (2), (14), and (15), allowing for unobserved random time-specific effects designed to capture potential spill-over effects and/or global shocks common to all countries (model 4). The ML-EIS estimation results obtained using a simulation sample size of $S = 100$ are summarized in Table 5.

The estimated marginal effects for all explanatory x_{it}-variables and the estimated variance parameter σ_τ of the time-invariant heterogeneity are very similar to those obtained under the models discussed above. Here again, we find no conclusive evidence for correlation between τ_i and $(\bar{x}_{i\cdot}, y_{i0})$. The results show a large and highly significant state-dependence effect similar to that found under the pure random country-specific effect model in Table 3. The variance parameter of the time factor σ_ξ and its autoregressive parameter δ are both highly significant, indicating that there are significant common dynamic time-specific effects in addition to state dependence. Hence, in contrast to the specification with state dependence and an AR country-specific error component, the model seems to be able to separate the two sources of persistence. Also, the estimated autocorrelation parameter of -0.89 implies a strong mean reversion in the common time-specific factor. This mean-reverting tendency in the common factor affects the common probability of experiencing a current account reversal across all countries and is, therefore, fully consistent with a global accounting restriction requiring that deficits and surpluses across all national current accounts need to be balanced. In particular, one would expect that a temporary simultaneous increase in the propensities to experience a large reduction in current account deficits is immediately reverted in order to guarantee a global balance in deficits and surpluses, rather than a persistent and long-lasting increase in individual propensities.

Although the time-specific factor capturing global shocks and/or contagion effects is significant, it appears to be quantitatively fairly small. In fact, the fraction of error variance due to the time-specific effect in only 3.5%. Therefore, it is not surprising that the overall fit of the model and its predicted dynamic effects (see, the lower right panel of Figure 1) do not change significantly relative to the pure random country-specific effect model in Table 3 which leaves out the time-specific effect.

Finally, we note that the quantitatively low impact of the common time-specific factor might be due to the implicit restriction that the loading w.r.t. that factor is the same across all countries. Hence, a natural extension of the model would be to allow for factor loadings, which differ across countries (whether randomly or deterministically). However, due to a substantial increase in the number of parameters or the dimension of the integration problem associated with the likelihood evaluation the statistical inference of such an extension is non-trivial without further restrictions and is left to future research.

6 Predictive Performance

Models 2 to 4 are essentially observationally equivalent with log-likelihood values ranging from -253.1 to -255.2. However, log-likelihood comparisons provide an incomplete picture of the overall quality of a binary model. Hence, we compare next models 2 to 4 on two predictive benchmarks: the proportion of correctly predicted binary outcomes and predicted duration distribution of reversal episodes.

Assessing the predictive performance of an estimated binary model requires selecting a threshold c whereby success (current account reversal) is predicted iff the predicted probability is larger than c, i.e., $r_{it} = \hat{p}(y_{it}|x_{it}, y_{it-1}) > c$. The corresponding classification error probabilities are given by

$$\alpha(c) = 1 - p(r_{it} > c|y_{it} = 1) \quad \text{and} \qquad \beta(c) = p(r_{it} > c|y_{it} = 0), \tag{22}$$

which can be approximated by the corresponding relative frequencies of misclassification. Since the sample portion Π of success is only of the order of 0.1, it does not make sense to select a threshold c which minimizes the unconditional probability of misclassification $p(c) = \Pi\alpha(c) + (1-\Pi)\beta(c)$. Following Winkelmann and Boes (2006), we first computed for each model the threshold c_* which minimizes the sum of classification error probabilities $\alpha(c) + \beta(c)$. We also computed their Receiver Operating Characteristic (ROC) curves, defined as the curves plotting $1 - \alpha(c)$ against $\beta(c)$, as well as the areas under these ROC curves. These areas have a minimum of 0.5 (complete randomness) and a maximum of 1 (errorless classification). The ROC curves are displayed in Figure 2 and associated results for the optimal threshold c_*, classification error probabilities for c_* and ROC areas are reported in Table 6.

Note that c_* ranges from 0.08 to 0.11, which are close to the sample proportion Π of 0.10. Model 3 with AR(1) country-specific errors without state-dependence has the best predictive performance with $\alpha(c_*) + \beta(c_*) = 0.27$ and a ROC area of 0.91 (the corresponding figures for the other models range from 0.36 to 0.43 and 0.85 to 0.88, respectively). Also its ROC curve dominates those of the other models. Based on the optimal threshold it correctly predicts 91% of the observed reversals and 82% of the non-reversals.

We also used each estimated model to simulate 20,000 fictitious panel data sets of the binary outcome conditional on the observed x_{it} variables in order to obtain accurate MC approximations of the predictive distributions of the duration of reversal episodes to be compared with the frequency distribution observed for the data (see Figure 3, and Table 6 for predicted average durations). It appears that models 2 and 4 have a better performance than model 3 with a better fit to the empirical distribution and predicted average durations closer to the observed average of 1.52. However, the differences across the models seem to be not large enough to overturn the ROC ranking. Thus, if the likelihood criterion, which by itself is fairly uninformative about the source of serial dependence, is supplemented by measures of predictive performance, the model with AR(1) country-specific shocks and without state-dependence appears to be the preferred specification.

7 Conclusion

This paper uses different non-linear panel data specifications in order to investigate the causes and dynamics of current account reversals in low- and middle-income countries. In particular, we analyze four sources of serial persistence: (i) a country-specific random effect reflecting time-invariant differences in institutional, political or economic factors; (ii) serially correlated transitory error component capturing persistent country-specific shocks; (iii) dynamic common time-specific factor effects, designed to account for potential spill-over effects and global shocks to all countries; and (iv) a state dependence component to control for the effect of previous events of current account reversal and to capture slow adjustments in international trade flows.

The likelihood evaluation of the panel models with country-specific random heterogeneity and serially correlated error components requires high-dimensional integration for which we use a generic Monte-Carlo integration technique known as Efficient Importance Sampling (EIS).

Our empirical results indicate that the static pooled probit model is strongly dominated by the alternative models with serial dependence. However, state-dependence and transitory country-specific errors are essentially observationally equivalent. Only if we include random time-specific effects into the model with state-dependence, we find that both sources of serial dependence are significant, even though the time-specific effect is small with limited effect on the overall fit of the model. On the other hand, our assessment of the ability to predict current account reversals provides strong support for the model with transitory country-specific errors and without state-dependence, which appears to present the best compromise between log-likelihood fit and predictive performance. Also, we do not find conclusive evidence for the existence of random country-specific effects.

Overall, our results relative to the determinants of current account reversals are in line with the those in the empirical literature on current account crises and confirm the empirical relevance of theoretical solvency and sustainability considerations w.r.t. a country's trade balance. In particular, countries with high current account imbalances, low foreign reserves, a small fraction of concessional debt, and unfavorable terms of trades are more likely to experience a current account reversal. These results are fairly robust against the dynamic specification of the model.

Acknowledgement

We are grateful to an anonymous referee for his helpful comment which have produced major clarifications on several key issues. Roman Liesenfeld and Guilherme V. Moura acknowledge research support provided by the Deutsche Forschungsgemeinschaft (DFG) under grant HE 2188/1-1; Jean-François Richard acknowledges the research support provided by the National Science Foundation (NSF) under grant SES-0516642.

Appendix: EIS for random effects and serially correlated errors

This appendix details the implementation of the EIS procedure for the panel probit model (2) and (8) to obtain MC estimates for the likelihood contribution $I_i(\theta)$ given by equation (9) (for a detailed description of the EIS principle, see Richard and Zhang, 2007). In order to simplify the following presentation it proves convenient to omit the country index i and to relabel τ as λ_0. Then the likelihood integral in Equation (9) can be rewritten as

$$I(\theta) = \int_{\mathbb{R}^{T+1}} \prod_{t=0}^{T} \varphi_t(\underline{\lambda}_t) d\underline{\lambda}, \tag{A-1}$$

where $\varphi_0(\lambda_0) = f_\tau(\tau)$. Next, we partition $\underline{\lambda}'_t$ into $(\epsilon_t, \underline{\eta}'_{t-1})$ with $\underline{\eta}'_{t-1} = (\epsilon_{t-1}, \lambda_0)$ for $t > 1$, $\eta_0 = \lambda_0$ and $\eta_{-1} = \emptyset$. EIS is based upon a sequence of auxiliary importance sampling densities of the form

$$m_t(\epsilon_t | \underline{\eta}_{t-1}; a_t) = \frac{k_t(\underline{\lambda}_t; a_t)}{\chi_t(\underline{\eta}_{t-1}; a_t)}, \quad \text{with} \quad \chi_t(\underline{\eta}_{t-1}; a_t) = \int_{\mathbb{R}^1} k_t(\underline{\lambda}_t; a_t) d\epsilon_t, \tag{A-2}$$

for $t = 0, ..., T$, where $\{k_t(\underline{\lambda}_t; a_t); a_t \in A_t\}$ denotes a (pre-selected) class of auxiliary parametric density kernels with analytical integrating factor in ϵ_t given $(\underline{\eta}_{t-1}, a_t)$ denoted by $\chi_t(\underline{\eta}_{t-1}; a_t)$.

Let $\{\tilde{\underline{\lambda}}^{(j)} = \{\tilde{\underline{\lambda}}_t^{(j)}\}_{t=0}^{T}\}_{j=1}^{S}$ be S independent trajectories drawn from the auxiliary sampler $m(\underline{\lambda}|a) = \prod_{t=0}^{T} m_t(\epsilon_t|\underline{\eta}_{t-1}; a_t)$. The corresponding Importance Sampling MC estimate of $I(\theta)$ obtains as:

$$\bar{I}_S(\theta) = \chi_0(a_0) \frac{1}{S} \sum_{j=1}^{S} \left[\prod_{t=0}^{T} \frac{\varphi_t(\tilde{\underline{\lambda}}_t^{(j)}) \chi_{t+1}(\tilde{\underline{\eta}}_t^{(j)}; a_{t+1})}{k_t(\tilde{\underline{\lambda}}_t^{(j)}; a_t)} \right]. \tag{A-3}$$

An Efficient Importance Sampler is one which minimizes the MC sampling variances of the ratios $\varphi_t \chi_{t+1}/k_t$ w.r.t. the auxiliary parameters $\{a_t\}_{t=0}^{T}$ under such draws. An approximate solution to this minimization problem, say $\{\hat{a}_t\}_{t=0}^{T}$, obtains by a sequence of $T+1$ back recursive regressions. In particular, in each period $t = T, ..., 0$ one needs to regress

$$\ln[\varphi_t(\tilde{\underline{\lambda}}_t^{(j)})\chi_{t+1}(\tilde{\underline{\eta}}_t^{(j)}; \hat{a}_{t+1})] \quad \text{on:} \quad \text{intercept}, \ \ln k_t(\tilde{\underline{\lambda}}_t^{(j)}, a_t), \tag{A-4}$$

where $\{\tilde{\underline{\lambda}}^{(j)}\}_{j=1}^{S}$ are drawn from an initial sampler $m(\underline{\lambda}|a_0)$. As an initial sampler we use the GHK sampling densities and the EIS sequence is iterated until obtainment of a fixed point in $\{\hat{a}_t\}_{t=0}^{T}$.

The kernel $k_t(\underline{\lambda}_t; a_t)$ in Equation (A-2) is selected to be a parametric extension of the period-t integrand φ_t in Equation (A-1). The latter includes a (truncated) Gaussian kernel in $\underline{\lambda}_t$. Hence, k_t is specified as

$$k_t(\underline{\lambda}_t; a_t) = \varphi_t(\underline{\lambda}_t) \cdot \zeta_t(\underline{\lambda}_t; a_t), \tag{A-5}$$

where ζ_t is itself a gaussian kernel in $\underline{\lambda}_t$. It follows that φ_t cancels out in the EIS regression (A-4). For the truncated Gaussian kernel k_t given in Equation (A-5) we use the following parametrization:

$$k_t(\underline{\lambda}_t; a_t) = \frac{\mathbb{I}(\epsilon_t \in D_t^*)}{\sqrt{2\pi}} \exp\{-\frac{1}{2}(\underline{\lambda}_t' P_t \underline{\lambda}_t + 2\underline{\lambda}_t' q_t)\}, \tag{A-6}$$

where $D_t^* = (-\infty \ , \ \gamma_t + \delta_t \lambda_0]$, with $\gamma_t = (2y_t - 1)\mu_t$ and $\delta_t = (2y_t - 1)$. The EIS parameter a_t consists of the six lower diagonal elements of P_t and the three elements in q_t. In what follows we make use of the Cholesky decomposition of P_t into

$$P_t = L_t \Delta_t L_t', \tag{A-7}$$

where $L_t = \{l_{ij,t}\}$ is a lower triangular matrix with ones on the diagonal and Δ_t is diagonal matrix with diagonal elements $d_{i,t} \geq 0$. Let

$$l_{1,t} = (l_{21,t}, l_{31,t})', \quad l_{2,t} = (1, l_{32,t})'. \tag{A-8}$$

The key step in our EIS implementation consists of finding the analytical expression of the integrating factor $\chi_t(\underline{\eta}_{t-1}; a_t)$ associated with the density kernel (A-6). It is the object of the following lemma.

Lemma 1. *The integral of $k_t(\underline{\lambda}_t; a_t)$ w.r.t. ϵ_t is of the form*

$$\chi_t(\underline{\eta}_{t-1}; a_t) = k_{2,t}(\lambda_0; a_t)[\Phi(\alpha_t + \beta_t' \underline{\eta}_{t-1}) \cdot k_{1,t}(\underline{\eta}_{t-1}; a_t)], \tag{A-9}$$

together with

$$k_{1,t}(\underline{\eta}_{t-1}; \cdot) = \exp\{-\frac{1}{2}(d_{2,t}\underline{\eta}_{t-1}' l_{2,t} l_{2,t}' \underline{\eta}_{t-1} + 2\underline{\eta}_{t-1}' l_{2,t} m_{2,t})\}, \tag{A-10}$$

$$k_{2,t}(\lambda_0; \cdot) = \exp\{-\frac{1}{2}(d_{3,t}\lambda_0^2 + 2m_{3,t}\lambda_0)\} \cdot r_t, \tag{A-11}$$

where

$$\alpha_t = \sqrt{d_{1,t}}(\gamma_t + \frac{m_{1,t}}{d_{1,t}}), \qquad \beta_t = \sqrt{d_{1,t}}(l_{1,t} + \delta_t \iota), \tag{A-12}$$

$$r_t = \frac{1}{\sqrt{d_{1,t}}} \exp\{\frac{1}{2}\frac{m_{1,t}^2}{d_{1,t}}\}, \quad m_t = \{m_{i,t}\} = L_t^{-1} q_t, \quad \iota' = (0,1). \tag{A-13}$$

Proof. The proof is straightforward under the Cholesky factorization introduced in (A-7), deleting the index t for the ease of notation. First we introduce the transformation $z = L'\underline{\lambda}$, whereby $z_1 = \epsilon + l_1'\underline{\eta}_{-1}$, $z_2 = l_2'\underline{\eta}_{-1}$, and $z_3 = \lambda_0$. Whence,

$$\begin{aligned} \chi(\underline{\eta}_{-1}; \cdot) &= \exp\Big\{-\frac{1}{2}\sum_{i=2}^{3}(d_i z_i^2 + 2m_i z_i)\Big\} \\ &\qquad \times \frac{1}{\sqrt{2\pi}} \int_{D_t^{**}} \exp\{-\frac{1}{2}(d_1 z_1^2 + 2m_1 z_1)\} dz_1, \end{aligned}$$

where $D_t^{**} = (-\infty\ ,\ \gamma_t + (l_{1,t} + \delta_t \iota)'\underline{\eta}_{-1}]$. Next, we complete the quadratic form in z_1 under the integral sign and introduce the transformation $v = \sqrt{d_1}[z_1 + (m_1/d_1)]$. The result immediately follows.□

Next, we provide the full details of the recursive EIS implementation.

· *Period* $t = T$: With $\chi_{T+1} \equiv 1$, the only component of k_T is φ_T itself. Whence,

$$P_T = e_\rho e_\rho' \quad \text{and} \quad q_T = 0, \quad \text{with} \quad e_\rho' = (1, -\rho, 0). \tag{A-14}$$

· *Period* t $(T > t > 1)$: Given Equation (A-9) in lemma 1, the product $\varphi_t \cdot \chi_{t+1}$ comprises the following factors: φ_t as defined in Equation (10), $k_{1,t+1}$ as given by

Equation (A-10) and $\Phi(\alpha_{t+1}+\beta'_{t+1}\underline{\eta}_t)$, where $(\alpha_{t+1},\beta_{t+1})$ are defined in Equation (A-12). The first two factors are already gaussian kernels. Furthermore, the term $\Phi(\cdot)$ depends on $\underline{\lambda}_t$ only through the linear combination $\beta'_{t+1}\underline{\eta}_t$. Whence, ζ_t in Equation (A-5) is defined as

$$\zeta_t(\underline{\lambda}_t;a_t) = k_{1,t+1}(\underline{\eta}_t,\cdot)\exp\left\{-\frac{1}{2}\left[a_{1,t}(\beta'_{t+1}\underline{\eta}_t)^2 + 2a_{2,t}(\beta'_{t+1}\underline{\eta}_t)\right]\right\}, \tag{A-15}$$

with $a_t=(a_{1,t},a_{2,t})$. It follows that $k_{1,t+1}$ also cancels out in the auxiliary EIS regressions (A-4) which simplifies into OLS of $\ln\Phi(\alpha_{t+1}+\beta'_{t+1}\underline{\eta}_t)$ on $\beta'_{t+1}\underline{\eta}_t$ and $(\beta'_{t+1}\underline{\eta}_t)^2$ together with a constant. From these EIS regressions one obtains estimated EIS values for $(a_{1,t},a_{2,t})$. Note that $\underline{\eta}_t$ can be written as

$$\underline{\eta}_t = A\underline{\lambda}_t, \quad \text{with} \quad A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{A-16}$$

It follows that the parameters of the EIS kernel k_t in Equation (A-6) are given by

$$\begin{aligned} P_t &= e_\rho e'_\rho + d_{2,t+1}A'l_{2,t+1}l'_{2,t+1}A + a_{1,t}A'\beta_{t+1}\beta'_{t+1}A && \text{(A-17)} \\ q_t &= A'l_{2,t+1}m_{2,t+1} + a_{2,t}A'\beta_{t+1}. && \text{(A-18)} \end{aligned}$$

Its integrating factor $\chi_t(\underline{\eta}_t;a_t)$ follows by application of lemma 1.

$\cdot$ *Period* $t=1$: The same principle as above applies to period 1, but requires adjustments in order to account for the initial condition. Specifically, we have $\underline{\lambda}_1 = \underline{\eta}_1 = (\epsilon_1,\lambda_0)'$, $\lambda_0=\eta_0\ (=\tau)$. This amounts to replacing A by I_2 in Equations (A-16) to (A-18). Whence, the kernel $k_1(\lambda_1,a_1)$ needs only be bivariate with

$$\begin{aligned} P_1 &= e_1e'_1 + d_{2,2}l_{2,2}l'_{2,2} + \hat{a}_{1,1}\beta_2\beta'_2 && \text{(A-19)} \\ q_1 &= l_{2,2}m_{2,2} + \hat{a}_{2,1}\beta_2, && \text{(A-20)} \end{aligned}$$

with $e'_1=(1,0)$. Essentially, P_1 and q_1 have lost their middle row and/or column. To avoid changing notation in lemma 1, the Cholesky decomposition of P_1 is parameterized as

$$L_1 = \begin{pmatrix} 1 & 0 \\ l_{31,1} & 1 \end{pmatrix}, \quad D_1 = \begin{pmatrix} d_{1,1} & 0 \\ 0 & d_{3,1} \end{pmatrix}, \quad l_{1,1} = l_{31,1}, \tag{A-21}$$

while $d_{2,2}$ and $l_{2,2}$ are now zero. Under these adjustments in notation, lemma 1 still applies with $k_2(\eta_0;\cdot) \equiv 1$ and β_1 reduced to the scalar

$$\beta_1 = \sqrt{d_{1,1}}(l_{1,1} + \delta_1). \tag{A-22}$$

· *Period* $t = 0$ (untruncated integral w.r.t. $\lambda_0 \equiv \tau$): Accounting for the back transfer of $\{k_{2,t}(\lambda_0;\cdot)\}_{t=1}^{T}$, all of which are gaussian kernels, the λ_0-kernel is given by

$$k_0(\lambda_0;\cdot) = f_\tau(\lambda_0) \cdot \prod_{t=1}^{T} k_{2,t}(\lambda_0;\cdot) \cdot \ \exp\{-\frac{1}{2}\left(\hat{a}_{1,0}\lambda_0^2 + 2\hat{a}_{2,0}\lambda_0\right)\}, \tag{A-23}$$

where $(\hat{a}_{1,0}, \hat{a}_{2,0})$ are the coefficients of the EIS approximation of $\ln \Phi(\alpha_1 + \beta_1\lambda_0)$. Note that k_0 is the product of $T+2$ gaussian kernels in λ_0 and is, therefore, itself a gaussian kernel, whose mean m_0 and variance v_0^2 trivially obtain by addition from Equation (A-23).

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Table 1. List of countries

Country	Initial Obs.	Final Obs.	Reversals	Country	Initial Obs.	Final Obs.	Reversals
Argentina	1988	2001	2	Jordan	1984	2001	4
Bangladesh	1984	2000	0	Kenya	1984	2001	2
Benin	1984	1999	2	Lesotho	1984	2000	0
Bolivia	1984	2001	3	Madagascar	1984	2001	0
Botswana	1984	2000	2	Malawi	1984	2001	0
Brazil	1984	2001	1	Malaysia	1984	2001	5
Burkina Faso	1984	1992	0	Mali	1991	2000	0
Burundi	1989	2001	0	Mauritania	1984	1996	4
Cameroon	1984	1993	0	Mexico	1984	2001	1
Central African Republic	1984	1992	0	Morocco	1984	2001	2
Chile	1984	2001	3	Niger	1984	1993	1
China	1986	2001	1	Nigeria	1984	1997	2
Colombia	1984	2001	4	Pakistan	1984	2001	3
Congo Rep.	1984	2001	2	Panama	1984	2001	2
Costa Rica	1984	2001	1	Paraguay	1984	2001	2
Cote d'Ivoire	1984	2001	5	Peru	1984	2001	2
Dominican Republic	1984	2001	2	Philippines	1984	2001	3
Ecuador	1984	2001	1	Rwanda	1984	2001	1
Egypt	1984	2001	3	Senegal	1984	2001	3
El Salvador	1984	2001	2	Seychelles	1989	2001	4
Gabon	1984	1997	3	Sierra Leone	1984	1995	0
Gambia	1984	1995	1	Sri Lanka	1984	1997	2
Ghana	1984	2001	1	Swaziland	1984	2001	3
Guatemala	1984	2001	0	Thailand	1984	2001	3
Guinea-Bissau	1987	1995	0	Togo	1984	2000	0
Haiti	1984	1998	3	Tunisia	1984	2001	2
Honduras	1984	2001	2	Turkey	1984	2001	0
Hungary	1986	2001	1	Uruguay	1984	2001	0
India	1984	2001	0	Venezuela	1984	2001	1
Indonesia	1985	2001	1	Zimbabwe	1984	1992	2

Table 2. ML-estimates of Model 1: Pooled probit

	Static		Dynamic	
Variable	Estimate	Marg. Eff.	Estimate	Marg. Eff.
Constant	-1.993^{***}		-1.955^{***}	
	(0.474)		(0.493)	
AVGCA	-0.060^{***}	-0.009	-0.060^{***}	-0.009
	(0.012)		(0.012)	
AVGGROW	0.008	0.001	0.009	0.001
	(0.021)		(0.021)	
AVGINV	-0.002	-0.0003	0.001	0.0001
	(0.010)		(0.011)	
AVGTT	-0.108	-0.017	-0.109	-0.016
	(0.066)		(0.069)	
GOV	0.026^{**}	0.004	0.018	0.003
	(0.012)		(0.012)	
OT	-0.011	-0.002	-0.011	-0.002
	(0.010)		(0.010)	
OPEN	-0.058	-0.009	-0.085	-0.012
	(0.087)		(0.090)	
USINT	0.108	0.017	0.107	0.015
	(0.073)		(0.075)	
GROWOECD	0.084	0.013	0.042	0.006
	(0.086)		(0.090)	
INTPAY	0.024	0.004	0.021	0.003
	(0.029)		(0.030)	
RES	-0.074^{**}	-0.011	-0.074^{**}	-0.011
	(0.030)		(0.030)	
CONCDEB	-0.165^{**}	-0.026	-0.152^{**}	-0.022
	(0.068)		(0.071)	
κ			0.981^{***}	0.209
			(0.158)	
Log-likelihood	-276.13		-257.26	

Note: The estimated model is given by Equation (2) assuming that the errors are independent across countries and time. The asymptotic standard errors are given in parentheses and obtained from the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level.

Table 3. ML-estimates of Model 2: Random country-specific effects

Variable	Estimate	Marg. Eff.
Constant	-1.880^{***}	
	(0.534)	
AVGCA	-0.064^{***}	-0.009
	(0.015)	
AVGGROW	0.010	0.001
	(0.021)	
AVGINV	-0.0001	-0.00001
	(0.011)	
AVGTT	-0.122	-0.017
	(0.084)	
GOV	0.018	0.003
	(0.012)	
OT	-0.011	-0.002
	(0.011)	
OPEN	-0.069	-0.010
	(0.093)	
USINT	0.083	0.012
	(0.075)	
GROWOECD	0.073	0.010
	(0.090)	
INTPAY	0.014	0.002
	(0.031)	
RES	-0.073^{**}	-0.010
	(0.035)	
CONCDEB	-0.159^{**}	-0.023
	(0.078)	
κ	0.982^{***}	0.206
	(0.154)	
σ_τ	0.162	
	(0.210)	
σ_e	1.013	
Log-likelihood	-254.47	
LR-statistic for $\mathrm{H}_0 : \sigma_\tau = 0$	5.57	
F-statistic for exogeneity of x_{it}	1.94	
t-statistic for exogeneity of y_{i0}	-2.01	

Note: The estimated model is given by Equations (2) and (3). The asymptotic standard errors are given in parentheses and obtained from the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1% and 5% critical values of the LR-statistic for $\mathrm{H}_0 : \sigma_\tau = 0$ are 5.41 and 2.71. The 1% and 5% critical values of the F-statistic (t-statistic) are 2.71 and 2.03 (2.68 and 2.01).

Table 4. ML-EIS estimates of Model 3: AR(1) country-specific errors.

	Dynamic		Static	
Variable	Estimate	Marg. Eff.	Estimate	Marg. Eff.
Constant	-1.795^{***}		-1.512^{**}	
	(0.567)		(0.677)	
AVGCA	-0.072^{***}	-0.010	-0.087^{***}	-0.012
	(0.018)		(0.021)	
AVGGROW	0.007	0.001	0.0001	0.00001
	(0.024)		(0.027)	
AVGINV	0.004	0.001	0.010	0.001
	(0.013)		(0.017)	
AVGTT	-0.161^{*}	-0.022	-0.251^{**}	-0.034
	(0.093)		(0.116)	
GOV	0.018	0.002	0.016	0.002
	(0.014)		(0.018)	
OT	-0.010	-0.001	-0.009	-0.001
	(0.012)		(0.014)	
OPEN	-0.108	-0.015	-0.175	-0.023
	(0.109)		(0.136)	
USINT	0.097	0.013	0.119	0.016
	(0.075)		(0.082)	
GROWOECD	0.057	0.008	0.038	0.005
	(0.087)		(0.095)	
INTPAY	0.029	0.004	0.045	0.006
	(0.035)		(0.037)	
RES	-0.097^{**}	-0.013	-0.143^{***}	-0.019
	(0.046)		(0.054)	
CONCDEB	-0.190^{**}	-0.026	-0.261^{***}	-0.035
	(0.088)		(0.099)	
κ	0.520^{*}	0.088		
	(0.297)			
σ_τ	0.142		0.194	
	(0.322)		(0.403)	
ρ	0.349^{*}		0.590^{***}	
	(0.198)		(0.090)	
σ_e	1.077		1.254	
Log-likelihood	-253.27		-255.17	
LR-statistic for $\mathrm{H}_0 : \rho = 0$	2.40		36.65	
F-statistic for exogeneity of x_{it}	2.16		2.54	
t-statistic for exogeneity of y_{i0}	-1.84			

Note: The estimated model is given by Equations (2) and (8). The ML-EIS estimation are based on a MC sample size of $S = 100$. The asymptotic standard errors are given in parentheses and obtained from the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1%, 5%, and 10% percent critical values of the LR-statistic for $\mathrm{H}_0 : \rho = 0$ are 6.63, 3.84, and 2.71. The 1% and 5% critical values of the F-statistic (t-statistic) are 2.71 and 2.03 (2.68 and 2.01).

Table 5. ML-EIS estimates of Model 4: AR(1) time-specific effects

Variable	Estimate	Marg. Eff.
Constant	-1.967^{***}	
	(0.677)	
AVGCA	-0.064^{***}	-0.009
	(0.014)	
AVGGROW	0.013	0.002
	(0.022)	
AVGINV	-0.001	-0.0001
	(0.011)	
AVGTT	-0.122	-0.017
	(0.075)	
GOV	0.018	0.003
	(0.012)	
OT	-0.010	-0.001
	(0.011)	
OPEN	-0.065	-0.009
	(0.095)	
USINT	0.070	0.010
	(0.071)	
GROWOECD	0.113	0.016
	(0.097)	
INTPAY	0.011	0.002
	(0.032)	
RES	-0.073^{**}	-0.010
	(0.035)	
CONCDEB	-0.163^{**}	-0.023
	(0.074)	
κ	1.013^{***}	0.210
	(0.139)	
σ_τ	0.154	
	(0.201)	
δ	-0.888^{***}	
	(0.041)	
σ_ξ	0.089^{**}	
	(0.048)	
σ_e	1.030	
Log-likelihood	-253.13	
F-statistic for exogeneity of x_{it}	2.09	
t-statistic for exogeneity of y_{i0}	-1.98	

Note: The estimated model is given by Equations (2), (14), and (15). The ML-EIS estimation are based on a MC sample size of $S = 100$. The asymptotic standard errors are given in parentheses and obtained from the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1% and 5% critical values of the F-statistic (t-statistic) are 2.71 and 2.03 (2.68 and 2.01).

Table 6. Classification errors and predicted average duration in years

	c_*	$\alpha(c_*)$	$\beta(c_*)$	ROC area	average duration
Model 2: Random country-specific effects	0.11	0.25	0.18	0.85	1.68 (0.12)
Model 3: AR(1) country-specific errors (static)	0.12	0.09	0.18	0.91	1.77 (0.14)
Model 3: AR(1) country-specific errors (dynamic)	0.09	0.11	0.25	0.88	1.80 (0.14)
Model 4: AR(1) time-specific effects	0.08	0.13	0.28	0.86	1.66 (0.12)

Note: Estimated standard deviation of the predicted average duration are given in parentheses. The observed average duration is 1.52 years.

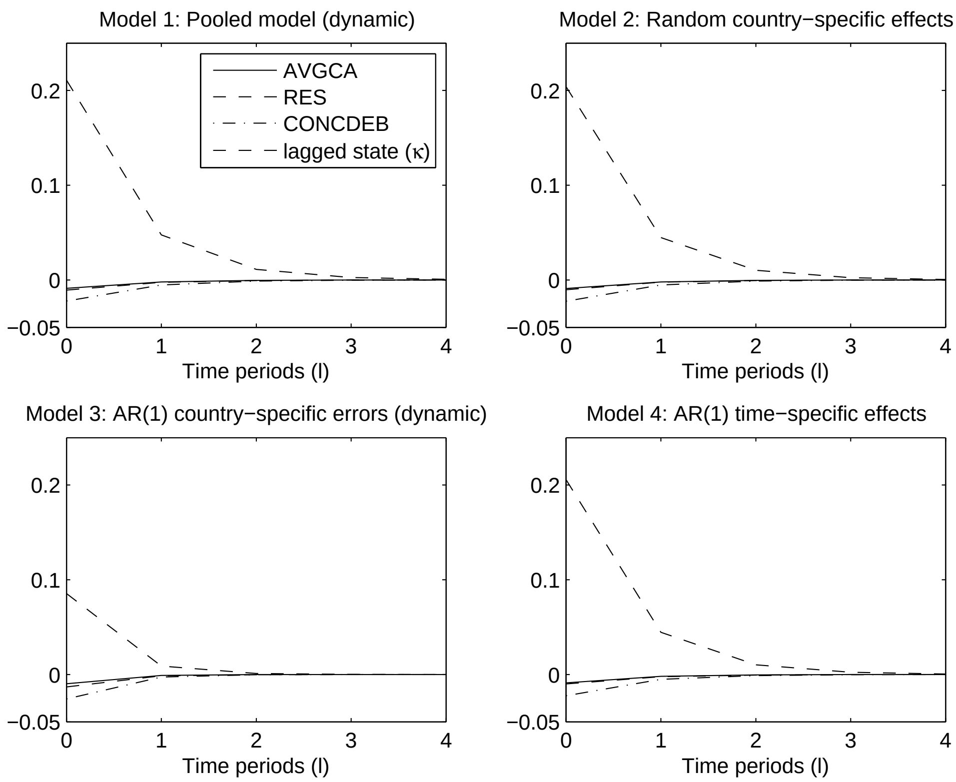

Figure 1: *Average ℓ-step ahead marginal effects of the covariates AVGCA, RES, CONCDEB and the lagged binary state variable computed according to Equations (19) and (20).*

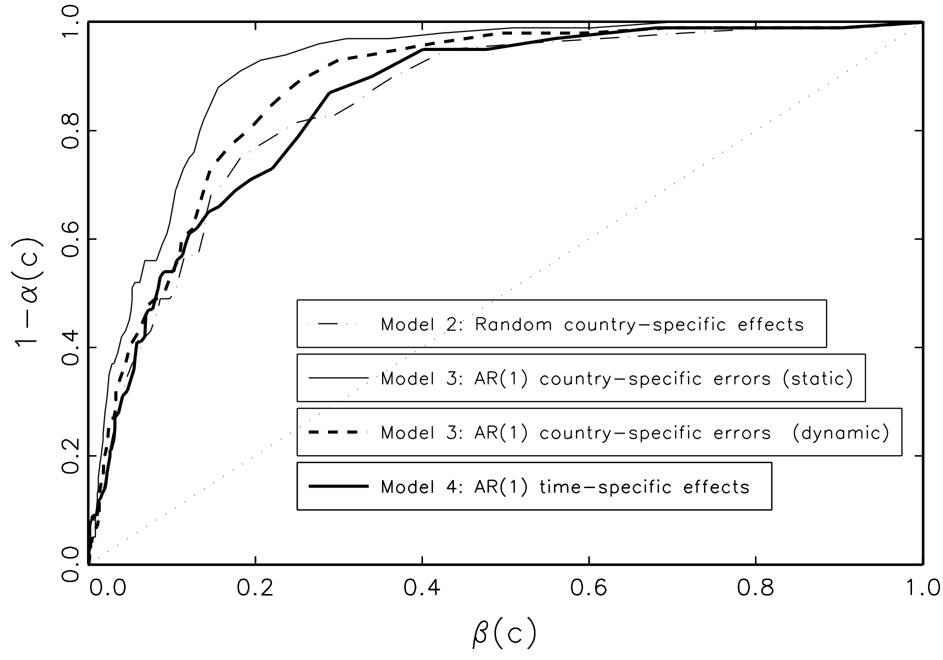

Figure 2: *Receiver Operating Characteristic curves for models 2 to 4.*

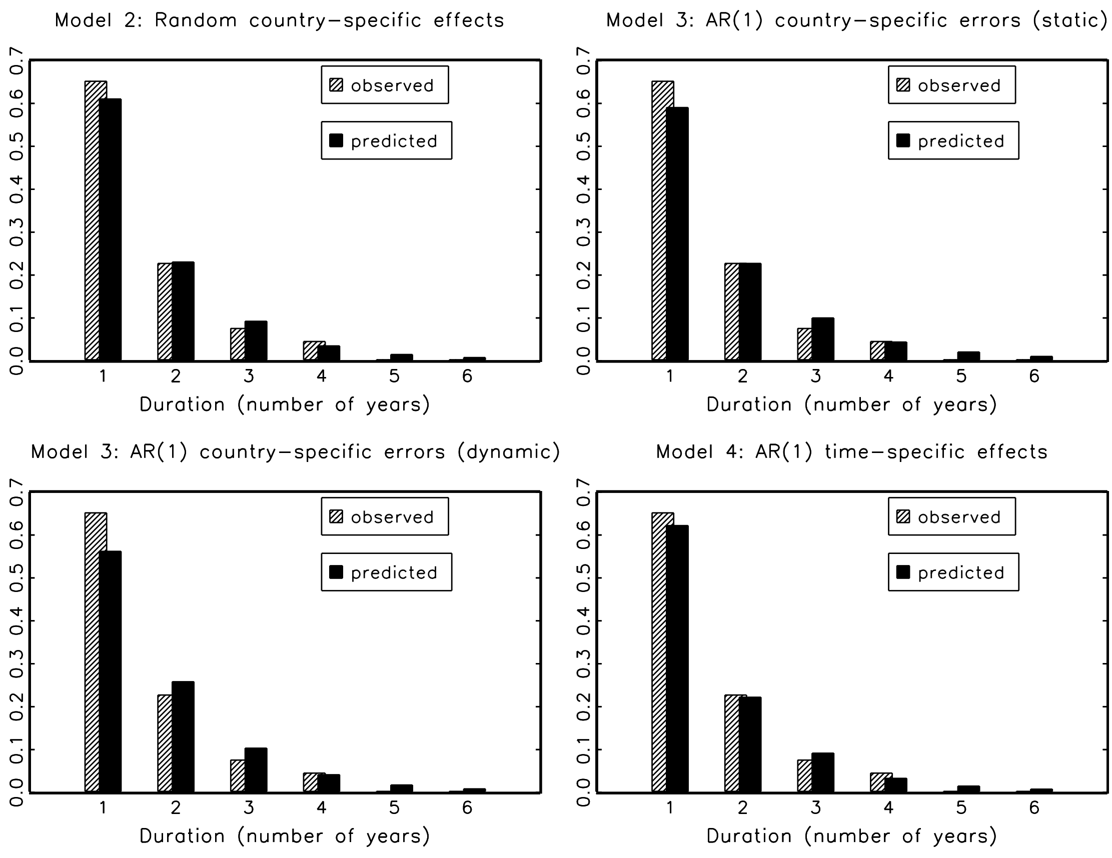

Figure 3: *Observed and predicted relative frequencies for the duration of reversal episodes for models 2 to 4. The observed average duration is 1.52 years.*