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Dynamic Panel Probit Models for Current Account Reversals and their Efficient Estimation

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Abstract

We use panel probit models with unobserved heterogeneity 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 evaluation of these models requires high-dimensional integration for which we use a generic procedure known as Efficient Importance Sampling (EIS). Our empirical results suggest that current account balance, terms of trades, foreign reserves and concessional debt are important determinants of the probability of current-account reversal. Furthermore we find under all specifications evidence for serially correlated error components and weak evidence for state dependence.

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

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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 since the currency crises of the 1990s, and have found renewed interest because of the huge current account deficit of the US in recent years. The importance of the current account comes from its interpretation as a restriction on countries' expenditure abilities. 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 serial dependence inherent to current account reversals.

Milesi-Ferretti and Razin (1998) and Edwards (2004a,b) use panel probit models 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. They use time and country specific dummies in order to account for heterogeneity. In addition to the fact that it requires estimation of a large number of parameters, a fixed effect approach raises two key issues of identification in the context of the data set we propose to use. First, it precludes the use of potentially important explanatory variables which are constant across countries or over time. Also, current account crises are typically rare events and have not been experienced by some of the countries included in our data set.

Following Heckman (1981a), Falcetti and Tudela (2006) argue that there are two distinct possible sources of serial dependence which ought to be taken into account in the context of a panel analysis of currency crisis: State dependence and persistent heterogeneity across countries. State dependence would reflect the possibility that past reversals could affect the probability of another reversal. Unobserved heterogeneity would reflect differences in institutional, political or relevant economic factors across countries which cannot be controlled for. However, as argued, e.g., by Hyslop (1999), serial dependence could also be transitory resulting from autocorrelation, whether specific to individual countries (idiosyncratic error component) or common to all (time random effect). Serial dependence in the idiosyncratic error component may arise from a persistence of the current account deficit itself as documented, e.g., by Edwards (2004b). Serially correlated time random effects account for possible dynamic spillover effects of current account crises. 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 controlling for alternative sources of persistence. Our starting point is a panel probit model with state dependence and persistent random heterogeneity. We then analyze the robustness of this model against the introduction of correlated idiosyncratic error components (Section 3.1) or correlated common time effects (Section 3.2).

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 integration. 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 effects by $T + N$, where N is the number of countries. Thus efficient likelihood estimation of such models typically relies upon Monte-Carlo (MC) integration techniques (see, e.g., Geweke and Keane, 2001 and the references therein). Various MC procedures have been proposed for the evaluation of such choice probabilities – see, e.g., Stern (1997) for a survey. The most popular among those is the GHK procedure which was developed by Geweke (1991), Hajivassiliou (1990), and Keane (1994) and which has been applied to the estimation of dynamic panel probit models, e.g., by Hyslop (1999), Greene (2004), and Falcetti and Tudela (2006). While conceptually simple and easy to program, the GHK procedure relies upon importance sampling densities which ignore critical information relative to the underlying dynamic structure of the model. This can lead to significant deterioration of numerical accuracy as the dimensionality of integration increases. In particular, Lee (1997) conducts a MC study of ML estimation under GHK likelihood evaluation for panel models with serially correlated errors and finds significant biases for longer panels.

In the present study we use Efficient Importance Sampling (EIS) methodology developed by Richard and Zhang (2007), which represents a powerful and generic high dimensional simulation technique. It is based on simple Least-Squares optimizations designed to maximize the numerical accuracy of the integral approximations associated with the likelihood. As such, EIS is particularly well suited to handle unobserved heterogeneity and serially correlated errors in panel probit models. In particular, as illustrated below, combining EIS with GHK substantially improves the numerical efficiency of the standard GHK allowing for reliable ML estimation of dynamic panel probit models even in applications with a very large time dimension.

In conclusion of our introduction, we note that there are a number of other studies which empirically analyze discrete events reflecting marcoeconomic and/or financial crises using non-linear panel models, including those of Calvo et al. (2004) on sudden stops and those of Eichengreen et al. (1995) and Frankel and Rose (1996) on currency crises. The study most closely related to this 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 among episodes of such crises. 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 describe the data set and introduce the definition of a current account reversal used in our analysis. Section 3 presents the dynamic panel probit models used to analyze current account reversals. In Section 4 we describe the implementation of EIS procedure in this context. Empirical results are discussed in section 5 and some conclusions are drawn in section 6.

2 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 smaller time dimensions. The minimum number of time periods for a country is 9, the maximum is 18 and the average is 16.5 for a total of 963 observations. The 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. Therefore, the initial conditions problem for the estimation of a dynamic discrete choice model including the lagged dependent variable, as discussed, e.g., by Heckman (1981b), does not arise here. The sources of the data are the World Bank's World Development Indicators (2005) and the Global Development Finance (2004).

Current account reversal 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 deficit is reduced to below 10%. The independent variables are standard in the literature and contain lagged macroeconomic, external, debt and foreign variables that are potential indicators of a reversal. 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 variables included are the share of consessional debt to total debt and interest payments relative to the GDP (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 data are 3-years averages, to ensure consistency with the way reversals are measured.

3 Empirical Specifications

The baseline specification we use for our analysis is a dynamic panel probit model of the form

$$y^*_{it} = x'_{it}\pi + \kappa y_{it-1} + e_{it}, \quad y_{it} = \mathcal{I}(y^*_{it} > 0), \quad i = 1, ..., N, \quad t = 1, ..., T, \quad (1)$$

where $\mathcal{I}(y^*_{it} > 0)$ 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. The error term e_{it} is assumed to be normally distributed with zero mean and a fixed variance. 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 is included to capture possible state dependence. It reflects the possibility that past current account crises could lead to changes in institutional, political or economic factors affecting the probability of another reversal.

3.1 Panel models with random country-specific effects

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}. However, countries have institutional differences such as property rights, tax systems which are difficult to control for and which might affect their individual propensity to experience a current account reversal. In order to take these differences into account, fixed or random effect panel models could be used. However, a fixed effect model based on country-specific dummy variables, such as the one used in the studies of Milesi-Ferretti and Razin (1998) and Edwards (2004a,b), requires the estimation of a large number of parameters, leading to a significant loss of degrees freedom. Furthermore, since our data set includes countries that never experienced a reversal (see Table 1), for which the dependent variable does not vary, the ML-estimator does not exist. This identification problem restricts the analysis to a random effect approach.

A prominent random effect model is that proposed by Butler and Moffitt (1982). It assumes the following specification for the error term in Equation (1):

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

The country-specific term τ_i captures possible permanent latent differences in the propensity to experience a reversal. Furthermore, 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}. Ignoring such correlation leads to inconsistent parameter estimates. Whence, the orthogonality condition between the random effect and the included regressors should be tested. An independence test is discussed further below.

Notice that the time-invariant heterogeneity component τ_i implies a cross-period correlation of the error term e_{it} which is constant for all pairs of periods and is given by $\text{corr}(e_{it}, e_{is}) = \sigma_\tau^2/(\sigma_\tau^2 + 1)$ for $t \neq s$ (see, e.g., Greene, 2003). Additional potential sources of serial dependence are transitory country-specific differences in the propensity to experience a reversal leading to serial correlation in the error component ϵ_{it} of Equation (2). Furthermore, the intertemporal characteristics of the current account itself (Obstfeld and Rogoff, 1996), and the evidence of sluggish behavior of the trade balance (Baldwin and Krugman, 1989) and of foreign direct investments (Dixit, 1992) might introduce further serial dependence in ϵ_{it}. Whence, in addition to the Butler-Moffitt specification (1) and (2), we assume here that e_{it} includes a serially correlated idiosyncratic error component according to

$$e_{it} = \tau_i + \epsilon_{it}, \qquad \epsilon_{it} = \rho\epsilon_{it-1} + \eta_{it}, \qquad \eta_{it} \sim \text{i.i.d.N}(0, 1), \tag{3}$$

where τ_i and η_{it} are independent among each other and also from the variables included in x_{it}. In order to ensure stationarity we assume that $|\rho| < 1$.

3.2 Panel model with random country- and time-specific effects

International capital markets, particularly those in emerging economies, appear volatile and subject to spillover effects. The currency crises of the 1990s and the way in which they rapidly spread across emerging markets including those rated as healthy economies by analysts and multilateral institutions, have brought interest in contagion effects (see 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 resulting from a decline in exports and an increase in imports (see Corsetti et al., 1999). These effects can lead to a deterioration of the current account in other countries. 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 try to avoid this competitiveness loss through a devaluation of their own currency. This appears to have happened during the East Asian crises in 1997 (Dornbusch et al., 2000).

The panel probit models introduced above do not account for such spillover effects since they ignore correlation across countries. In order to address this issue we also consider the following factor specification for the error e_{it} in the probit regression (1):

$$e_{it} = \tau_i + \xi_t + \epsilon_{it}, \qquad \epsilon_{it} \sim \text{i.i.d.N}(0, 1), \tag{4}$$

with

$$\xi_t = \delta\xi_{t-1} + \nu_t, \qquad \nu_t \sim \text{i.i.d.N}(0, \sigma_\xi^2), \tag{5}$$

where τ_i, ϵ_{it} and ν_t are mutually independent and independent from x_{it}. Furthermore, it is assumed that $|\delta| < 1$. The common dynamic factor ξ_t represents unobserved time-specific effects which induce correlation across countries, reflecting possible spillover effects. Note that this factor specification, which was also used in Liesenfeld and Richard (2007) for a microeconometric application, resembles the linear panel models with a factor structure as discussed, e.g., in Baltagi (2005) and primarily used for the analysis of macroeconomic data.

3.3 A note on normalization

In Equations (2) to (5), we followed the standard practice of normalizing the probit equation (1) by setting the variance of the residual innovations 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 rule.

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

$$\begin{aligned}
\text{Equation (2)} &: \quad \sigma_e^2 = 1 + \sigma_\tau^2 \\
\text{Equation (3)} &: \quad \sigma_e^2 = \frac{1}{1-\rho^2} + \sigma_\tau^2 \\
\text{Equations (4)+(5)} &: \quad \sigma_e^2 = 1 + \sigma_\tau^2 + \frac{\sigma_\xi^2}{1-\delta^2}.
\end{aligned}$$

These differences affect comparisons between estimated coefficients across models (but not between estimated probabilities). The implied correction factors do not exceed 11% for the results reported below. For the ease of comparison we shall report the estimated standard deviation σ_e of e_{it} for each model.

4 Maximum-Likelihood Estimation

ML estimation of the simple pooled panel probit model is straightforward and essentially the same as for a single equation probit model. Efficient parameter estimates can also be easily obtained for the Butler-Moffitt model (1) and (2). In particular, the choice probabilities are represented by one dimensional integrals, which can be evaluated conveniently by means of a quadrature procedure. Let $\underline{y} = \{\{y_{it}\}_{t=1}^T\}_{i=1}^N$ and $\underline{x} = \{\{x_{it}\}_{t=1}^T\}_{i=1}^N$. Let θ denote the parameter vector to be estimated. The likelihood function for the Butler-Moffitt random effect model is then given by

$$L(\theta; \underline{y}, \underline{x}) = \prod_{i=1}^N \left\{ \int_{\mathbb{R}^1} \prod_{t=1}^T \left[\Phi_{it}^{y_{it}} (1-\Phi_{it})^{(1-y_{it})} \right] \frac{1}{\sqrt{2\pi\sigma_\tau^2}} \exp\left\{ \frac{-\tau_i^2}{2\sigma_\tau^2} \right\} d\tau_i \right\}, \tag{6}$$

where $\Phi_{it} = \Phi(x_{it}'\pi + \kappa y_{it-1} + \tau_i)$, and $\Phi(\cdot)$ represents the cdf of the standardized normal distribution. 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 obtain estimates of the random country-specific effects τ_i. Those estimates can serve as the basis for validating the imposed orthogonality conditions between the τ_i's and the included regressors. In particular, the conditional expectation of τ_i given the sample information $(\underline{y}, \underline{x})$ is obtained as

$$\hat{\tau}_i = \mathrm{E}(\tau_i | \underline{y}, \underline{x}; \theta) = \frac{\int_{\mathbb{R}} \tau_i h_i(\underline{y}_i, \tau_i | \underline{x}_i; \theta) d\tau_i}{\int_{\mathbb{R}} h_i(\underline{y}_i, \tau_i | \underline{x}_i; \theta) d\tau_i}, \tag{7}$$

where h_i 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 (6). For the evaluation of the numerator and denominator by Gauss-Hermite, the parameters θ are set to their ML-estimates. An auxiliary regression of the estimated random effects $\hat{\tau}_i$ against the time average of the explanatory variables provides a direct test of the validity of the orthogonality condition between τ_i and $\underline{x}_i$.

In contrast to the Butler-Moffitt model, the computation of the likelihood for the model (1) and (3) with country-specific effects and a serially correlated idiosyncratic error component requires the evaluation of $(T+1)$-dimensional interdependent integrals, and that of the model (1), (4), and (5) with country-specific and time effects the evaluation of $(T+N)$-dimensional integrals. Efficient estimation of these models cannot be obtained by means of standard numerical integration procedures. Instead, we propose to use the EIS methodology of Richard and Zhang (2007). EIS is a highly accurate MC integration procedure developed for the evaluation of high-dimensional integrals and is, therefore, ideally suited for ML estimation of non-linear panel models with unobserved random heterogeneity and serially correlated errors.

In the following two subsections we provide a brief description of the EIS implementation in the context of ML estimation of the panel probit model with random country-specific effects and serially correlated idiosyncratic errors (subsection 4.1), and with random country-specific and time effects (subsection 4.2). For the general theory of EIS, see Richard and Zhang (2007).

4.1 ML-EIS for random country-specific effects and serially correlated errors

The likelihood function of the panel probit model defined by Equations (1) and (3) has the form $L(\theta; \underline{y}, \underline{x}) = \prod_{i=1}^{N} I_i(\theta)$, where I_i represents the likelihood contribution of country i. In the following, we derive the likelihood function for a single country, deleting the subscript i for the ease of notation. Let $\underline{\lambda}' = (\tau, \epsilon_1, ..., \epsilon_T)$ and $\mu_t = x_t'\pi + \kappa y_{t-1}$. Under the assumption that $\epsilon_0 = 0$ the likelihood function is given by

$$I(\theta) = \int_{\mathbb{R}^{T+1}} \prod_{t=1}^{T} \varphi_t(\underline{\lambda}_t) f_\tau(\tau) d\underline{\lambda}, \tag{8}$$

where $\underline{\lambda}_t' = (\epsilon_t, \epsilon_{t-1}, \tau)$, $\underline{\lambda}_1' = (\epsilon_1, \tau)$ and

$$\varphi_t(\underline{\lambda}_t) = \begin{cases} \mathcal{I}(\epsilon_t \in D_t)\phi(\epsilon_t - \rho\epsilon_{t-1}), & \text{if} \quad t > 1 \\ \mathcal{I}(\epsilon_1 \in D_1)\phi(\epsilon_1), & \text{if} \quad t = 1 \end{cases} \tag{9}$$

$$D_t = \begin{cases} [-(\mu_t + \tau)\ ,\ \infty), & \text{if} \quad y_t = 1 \\ (-\infty\ ,\ -(\mu_t + \tau)], & \text{if} \quad y_t = 0. \end{cases} \tag{10}$$

$\mathcal{I}(\cdot)$ denotes the indicator function and $\phi(\cdot)$ the standardized Normal density. $I(\theta)$ will be evaluated by Importance Sampling under trajectories $\{\tilde{\underline{\lambda}}^{(j)}\}_{j=1}^{S}$ drawn from an Efficient Importance Sampling density $m(\underline{\lambda}|\cdot)$ constructed as described in Richard and Zhang (2007). In order to simplify the application of sequential EIS to the integral in (8) it proves convenient to relabel τ as λ_0 and to rewrite the integral as

$$I(\theta) = \int_{\mathbb{R}^{T+1}} \prod_{t=0}^{T} \varphi_t(\underline{\lambda}_t) d\underline{\lambda}, \tag{11}$$

where $\varphi_0(\lambda_0) = f_\tau(\tau)$. Also 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 aims at constructing a sequence of auxiliary importance samplers of the form

$$m_t(\epsilon_t|\underline{\eta}_{t-1}; a_t) = \frac{k_t(\underline{\lambda}_t; a_t)}{\chi_t(\underline{\eta}_{t-1}; a_t)}, \quad t = 0, ..., T, \tag{12}$$

with

$$\chi_t(\underline{\eta}_{t-1}; a_t) = \int_{\mathbb{R}} k_t(\underline{\lambda}_t; a_t) d\epsilon_t, \tag{13}$$

where $\{k_t(\underline{\lambda}_t; a_t); a_t \in A_t\}$ denote a (pre-selected) class of auxiliary parametric density kernels with $\chi_t(\underline{\eta}_{t-1}; a_t)$ as analytical integrating factor in ϵ_t given $(\underline{\eta}_{t-1}, a_t)$. The integral in (11) is rewritten as

$$I(\theta) = \chi_0(a_0) \int_{\mathbb{R}^{T+1}} \prod_{t=0}^{T} \left[\frac{\varphi_t(\underline{\lambda}_t) \chi_{t+1}(\underline{\eta}_t; a_{t+1})}{k_t(\underline{\lambda}_t; a_t)} \right] m_t(\epsilon_t|\underline{\eta}_{t-1}; a_t) d\underline{\lambda} \tag{14}$$

with $\chi_{T+1}(\cdot) \equiv 1$. The backward transfer of the integrating factors $\chi_{t+1}(\cdot)$ constitutes the cornerstone of sequential EIS and is meant to capture as closely as possible the dynamics of the underlying process. As discussed further below, it is precisely the lack of such transfers which explains the inefficiency of the GHK procedure in (large dimensional) interdependent truncated integrals. Under (14), an EIS-MC estimate of $I(\theta)$ is given by

$$\bar{I}_S(\theta) = \chi_0(a_0)\frac{1}{S}\sum_{j=1}^{S}\left[\prod_{t=0}^{T}\frac{\varphi_t(\underline{\tilde{\lambda}}_t^{(j)})\chi_{t+1}(\underline{\tilde{\eta}}_t^{(j)}; a_{t+1})}{k_t(\underline{\tilde{\lambda}}_t^{(j)}; a_t)}\right], \tag{15}$$

where $\{\underline{\tilde{\lambda}}^{(j)} = \{\underline{\tilde{\lambda}}_t^{(j)}\}_{t=0}^{T}\}_{j=1}^{S}$ denote S i.i.d. trajectories drawn from the auxiliary sampler

$$m(\underline{\lambda}|a) = \prod_{t=0}^{T} m_t(\epsilon_t|\underline{\eta}_{t-1}; a_t), \quad a = (a_0, ..., a_T) \in A = \times_{t=0}^{T} A_t. \tag{16}$$

That is to say, $\tilde{\epsilon}_t^{(j)}$ is drawn from $m_t(\epsilon_t|\underline{\tilde{\eta}}_{t-1}^{(j)}; a_t)$ for $t = 0, ..., T$. An Efficient Importance Sampler is one which minimizes the MC sampling variances of the ratios $\varphi_t\chi_{t+1}/k_t$ under such draws. Since $m_t(\cdot; a_t)$ depends itself upon a_t, efficient a_t's obtain as solutions of the following fixed point sequences of back-recursive auxiliary least squares (LS) problems:

$$\begin{aligned}(\hat{c}_t^{(k+1)}, \hat{a}_t^{(k+1)}) \;=\; \arg\min_{c_t, a_t}\sum_{j=1}^{S}\Big\{ & \ln\left[\varphi_t\big(\underline{\tilde{\lambda}}_t^{(k,j)}\big)\cdot\chi_{t+1}\big(\underline{\tilde{\eta}}_t^{(k,j)}; \hat{a}_{t+1}^{(k+1)}\big)\right] \\ & - c_t - \ln k_t\big(\underline{\tilde{\lambda}}_t^{(k,j)}; a_t\big)\Big\}^2,\end{aligned} \tag{17}$$

for $t = T, T-1, ..., 0$, where $\{\underline{\tilde{\lambda}}^{(k,j)} = \{\underline{\tilde{\lambda}}_t^{(k,j)}\}_{t=0}^{T}\}_{j=1}^{S}$ denote trajectories drawn from $m(\underline{\lambda}|\hat{a}^{(k)})$. Convergence to a fixed point solution typically requires 3 to 5 iterations for reasonably well-behaved applications. See Richard and Zhang (2007) for details. As starting values we propose to use those values for the auxiliary parameters a implied by the GHK sampling densities discussed further below.

Two additional key components of this EIS algorithm are as follows: (i) The kernel $k_t(\underline{\lambda}_t; a_t)$ has to approximate the ratio $\varphi_t(\underline{\lambda}_t) \cdot \chi_{t+1}(\underline{\eta}_t; a_{t+1})$ with respect to $\underline{\lambda}_t$, not just ϵ_t in order to capture the interdependence across the ϵ_t's. (There is no revisiting of period t once $\hat{a}_t$ has been found); (ii) All trajectories $\{\underline{\tilde{\lambda}}^{(k,j)}\}_{j=1}^S$ have to be obtained by transformation of a single set of Common Random Numbers (CRNs) $\{\underline{\tilde{u}}^{(j)}\}_{j=1}^S$ pre-drawn from a canonical distribution, i.e. one which does not depend on a. In the present case the CRNs consist of draws from a uniform distribution to be transformed into (truncated) gaussian draws from $m_t(\epsilon_t|\underline{\tilde{\eta}}_{t-1}; \hat{a}_t)$ (see Appendix 1).

Next, we discuss the specific application of EIS to the likelihood integral defined by Equation (8). In the present section, we only present the heuristic of such implementation. Full details are given in Appendix 1, where we show that the EIS problem in (17) actually reduces to a univariate EIS (instead of a trivariate one in $\underline{\lambda}_t$) by taking full advantage of the particular structure of $\chi_{t+1}(\cdot)$.

Note first that the period-t integrand in Equation (8) includes a (truncated) gaussian kernel. Therefore, it appears appropriate to select a gaussian kernel for $k_t(\underline{\lambda}_t; a_t)$, a choice further supported by the fact that we shall demonstrate that $\chi_t(\underline{\eta}_t; a_t)$ then takes the form of a gaussian kernel times a probability. Moreover, the selection of a gaussian kernel enables us to take full advantage of the fact that the class of gaussian kernels in $\underline{\lambda}_t$ is closed under multiplication (see DeGroot, 1970). Therefore, we specify k_t as the following product

$$k_t(\underline{\lambda}_t; a_t) = \varphi_t(\underline{\lambda}_t) \cdot k_{0,t}(\underline{\lambda}_t; a_t), \tag{18}$$

where $k_{0,t}$ is itself a gaussian kernel in $\underline{\lambda}_t$. It immediately follows that $\varphi_t \cdot \chi_{t+1}/k_t \equiv \chi_{t+1}/k_{0,t}$ so that φ_t cancels out in the auxiliary EIS-LS optimization problem as defined in Equation (17). Under specification (18), we follow the standard EIS implementation as described above, but need to pay attention to the fact that $\lambda_0 = \tau$ is present in all $T+1$ factors of the integrand. Whence, we proceed as follows:

(i) We regroup all terms in k_t which only depend on λ_0. Let denote the corresponding factorization as

$$k_t(\underline{\lambda}_t; a_t) = k_{1,t}(\underline{\lambda}_t; a_t) \cdot k_{3,t}(\lambda_0; a_t); \tag{19}$$

(ii) Let $\chi_{1,t}$ denote the integral of $k_{1,t}$ w.r.t. ϵ_t such that

$$\chi_{1,t}(\underline{\eta}_{t-1}; a_t) = \int_{\mathbb{R}} k_{1,t}(\underline{\lambda}_t; a_t) d\epsilon_t. \tag{20}$$

Note that this integral is truncated to D_t due to the indicator function $\mathcal{I}(\epsilon_t \in D_t)$ which is included in φ_t and, therefore, in $k_{1,t}$. Since $k_{1,t}$ is symmetric in ϵ_t, the (conditional) probability that $\epsilon_t \in D_t$ is the same as that of $\epsilon_t \in D_t^*$, where

$$D_t^* = (-\infty\ ,\ \gamma_t + \delta_t \lambda_0], \quad \text{with} \quad \gamma_t = (2y_t - 1)\mu_t, \quad \delta_t = (2y_t - 1). \tag{21}$$

It follows that $\chi_{1,t}$ takes the form of a gaussian kernel in $\underline{\eta}_{t-1}$ times the probability that $\epsilon_t \in D_t^*$ conditional on $\underline{\eta}_{t-1}$, say

$$\chi_{1,t}(\underline{\eta}_{t-1}; a_t) = \Phi(\alpha_t + \beta_t' \underline{\eta}_{t-1}) \cdot k_{2,t}(\underline{\eta}_{t-1}; a_t), \tag{22}$$

where (α_t, β_t') are appropriate functions of a_t and the data.

It follows from Equations (19) to (22) that the integral of k_t w.r.t. ϵ_t is of the form

$$\chi_t(\underline{\eta}_{t-1}; a_t) = k_{3,t}(\lambda_0; a_t)[\Phi(\alpha_t + \beta_t' \underline{\eta}_{t-1}) \cdot k_{2,t}(\underline{\eta}_{t-1}; a_t)]. \tag{23}$$

In direct application of the backward transfer of integrating factors associated with sequential EIS, the factor $k_{3,t}$ is transferred back directly into the period $t = 0$ integral while the two factors between brackets are transferred back into the period $t - 1$ integral. Full details are provided in Appendix 1.

The EIS procedure can also be used to obtain an accurate MC-estimate of the conditional expectation of $\tau|\underline{y}, \underline{x}$ according to Equation (7). Under the panel probit model (1) and (3), the joint conditional pdf of $\underline{y}$ and τ given $\underline{x}$ takes the form

$$h(\underline{y}, \tau|\underline{x}; \theta) = \left[\int_{\mathbb{R}^T} \prod_{t=1}^{T} \varphi_t(\underline{\lambda}_t) d\epsilon_1 \cdots d\epsilon_T \right] f_\tau(\tau), \tag{24}$$

which is used in Equation (7) in order to produce MC-EIS estimates of the conditional expectation of τ.

We conclude this heuristic presentation of the EIS-application to the panel probit model defined by Equations (1) and (3) with two important comments. Firstly, as mentioned above, the MC procedure most frequently used to compute choice probabilities is the GHK technique. It is also an importance sampling procedure but it selects φ_t itself as the auxiliary period-t kernel. The corresponding importance sampling density is given by

$$m_t(\epsilon_t|\underline{\eta}_{t-1}) = \frac{\varphi_t(\underline{\lambda}_t)}{\Phi(\gamma_t + \delta_t \lambda_0 + \delta_t \rho \epsilon_{t-1})}, \quad t = 1, ..., T, \tag{25}$$

and $m_0(\lambda_0) = f_\tau(\tau)$ for period $t = 0$. The GHK-MC estimate of $I(\theta)$ is then obtained as

$$\bar{I}_S(\theta) = \frac{1}{S} \sum_{j=1}^{S} \left[\prod_{t=1}^{T} \Phi(\gamma_t + \delta_t \tilde{\lambda}_0^{(j)} + \delta_t \rho \tilde{\epsilon}_{t-1}^{(j)}) \right], \tag{26}$$

where $\{\tilde{\underline{\lambda}}^{(j)}\}_{j=1}^{S}$ denotes i.i.d. trajectories drawn from the sequential samplers $(m_0(\lambda_0),\ \{m_t(\epsilon_t|\underline{\eta}_{t-1})\}_{t=1}^{T})$. Note that the GHK importance sampler actually belongs to the class of auxiliary EIS samplers introduced in Equation (18) since it amounts to selecting a diffuse $k_{0,t} \propto 1$. Therefore, it is inefficient within this class. Results of a MC experiment provided in Appendix 2 highlight the inefficiency of GHK in the context of the particular model analyzed here. A broader MC investigation of the relative inefficiency of GHK relative to EIS belongs to our research agenda.

Secondly, Zhang and Lee (2004) offer a MC comparison between GHK and AGIS, where AGIS denotes an earlier version of EIS, in the context of the same model as that defined in Equations (1) and (3). In apparent contrast with the results presented below, they find that GHK performs essentially as well as AGIS, except for longer panels. However, their AGIS algorithm differs from our EIS implementation in several critical aspects. Most importantly, it ignores the factorization (19) and has no direct transfer of integrating factors depending solely on $\lambda_0 = \tau$. This turns out to be a major source of inefficiency since critical information relative to τ is then filtered through the full sequence of AGIS approximations instead of being transferred directly back into the $t = 0$ integral. Moreover, it would appear that AGIS optimizations are not iterated toward fixed point solutions as in Equation (17), nor does AGIS relies upon CRNs. Last but not least, the simulation results in Zhang and Lee are based upon i.i.d. replications of the actual sampling process (with no indications as to how the auxiliary AGIS draws are produced across replications). Whence, the standard deviations and/or mean squared errors they report are measures of conventional statistical dispersions with no indications of numerical accuracy. In contrast, the results reported below are based upon i.i.d. replications of the CRNs for a given sample and are, therefore, meant to measure only numerical accuracy. See Richard and Zhang (2007) for a discussion of the importance of these additional EIS refinements.

4.2 ML-EIS for random country-specific and time effects

The likelihood function for the random effect panel model consisting of Equations (1), (4), and (5) is given by

$$L(\theta; \underline{y}, \underline{x}) = \int_{\mathbb{R}^{T+N}} \prod_{i=1}^{N} \prod_{t=1}^{T} [\Phi(z_{it})]^{y_{it}} [1 - \Phi(z_{it})]^{(1-y_{it})} p(\underline{\tau}, \underline{\xi}) d\underline{\tau}, d\underline{\xi}, \tag{27}$$

with $\underline{\xi} = \{\xi_t\}_{t=1}^{T}$, $\underline{\tau} = \{\tau_i\}_{i=1}^{N}$ and $z_{it} = x_{it}'\pi + \kappa y_{it-1} + \tau_i + \xi_t$. 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. We assume that the τ_i's are independent across countries but allow for correlation among $\underline{\xi}$. Whence, the joint density of $(\underline{\tau}, \underline{\xi})$ is assumed to be proportional to

$$p(\underline{\tau}, \underline{\xi}) \propto \sigma_\tau^{-N} \exp\left\{-\frac{1}{2\sigma_\tau^2}\tau_i^2\right\} |H_\xi|^{\frac{1}{2}} \exp\left\{-\frac{1}{2}\underline{\xi}' H_\xi \underline{\xi}\right\}, \tag{28}$$

where H_ξ denotes the precision matrix of $\underline{\xi}$. See Richard (1977) for analytical expressions of H_ξ under alternative initial conditions, including stationarity. Conditionally on $\underline{\xi}$, one could apply GHK to each country individually, though Gauss-Hermite would likely be more efficient for these univariate integrals in τ_i. One would then be left with a complicated T-dimensional integral in $\underline{\xi}$. In contrast, EIS can be applied to the likelihood function (27) in a way which effectively captures the complex interdependence between $\underline{\tau}$ and $\underline{\xi}$. We shall just outline the main steps of this EIS implementation. See Richard and Zhang (2007) or Liesenfeld and Richard (2007) for details.

The integrand in Equation (27) is first factorized as follows

$$L(\theta; \underline{y}, \underline{x}) = \int_{\mathbb{R}^{T+N}} \phi_0(\underline{\xi}) \prod_{i=1}^{N} \phi_i(\tau_i, \underline{\xi}) d\underline{\tau} d\underline{\xi}, \tag{29}$$

where

$$\phi_0(\underline{\xi}) \quad \propto \quad |H_\xi|^{\frac{1}{2}} \exp\left[-\frac{1}{2}\underline{\xi}' H_\xi \underline{\xi}\right] \tag{30}$$

$$\phi_i(\tau_i, \underline{\xi}) \quad \propto \quad \sigma_\tau^{-1} \exp\left[-\frac{1}{2\sigma_\tau^2}\tau_i^2\right] \prod_{t=1}^{T} [\Phi(z_{it})]^{y_{it}} [1 - \Phi(z_{it})]^{(1-y_{it})}. \tag{31}$$

It is critical that the EIS sampler $m(\underline{\tau}, \underline{\xi}; a)$ fully reflects the interdependence structure of the posterior density of $(\underline{\tau}, \underline{\xi})$ which is proportional to the integrand in Equation (29). Specifically, the τ_i's are independent from one another *conditionally* on $\underline{\xi}$ but are individually linked to the full $\underline{\xi}$-vector. Accordingly, the auxiliary sampler is factorized as

$$m(\underline{\tau}, \underline{\xi}; a) = m_0(\underline{\xi}; a_0) \prod_{i=1}^{N} m_i(\tau_i | \underline{\xi}; a_i). \tag{32}$$

The corresponding kernels $\{k_i(\tau_i, \underline{\xi}; a_i)\}_{i=1}^{N}$ and $k_0(\underline{\xi}; a_0)$ are specified as *joint* gaussian kernels in $(\tau_i, \underline{\xi})$ and $\underline{\xi}$, respectively. Significant simplifications follow from the particular form of the integrand in Equation (29). First, note that $\ln \phi_i$ is given by

$$\ln \phi_i(\tau_i, \underline{\xi}) \propto -\frac{1}{2}\frac{\tau_i^2}{\sigma_\tau^2} + \sum_{t=1}^{T} \ln \left\{[\Phi(z_{it})]^{y_{it}} [1 - \Phi(z_{it})]^{(1-y_{it})}\right\}. \tag{33}$$

Each factor in the sum depends only on a single z_{it}. Therefore, $\ln k_i$ is specified as follows

$$\ln k_i(\tau_i, \underline{\xi}; a_i) = -\frac{1}{2}\left[\frac{\tau_i^2}{\sigma_\tau^2} + \sum_{t=1}^{T}(\alpha_{i,t} z_{i,t}^2 + 2\beta_{i,t} z_{i,t})\right] \tag{34}$$

for a total of $2 \cdot T$ auxiliary parameters plus the intercept. It follows that, at the cost of standard algebraic operations $\chi_i(\underline{\xi}; a_i)$ (i.e. the integrating constant for k_i) is itself a gaussian kernel in $\underline{\xi}$. Whence, the product $\phi_0(\underline{\xi}) \cdot \prod_{i=1}^{N} \chi_i(\underline{\xi}; a_i)$ is a gaussian kernel and requires no further adjustment (an interesting example of perfect fit in an EIS auxiliary regression).

Estimates for the unobserved random effects are obtained, in the same way as under the panel model without time effects, as by-products of the ML-EIS parameter estimates. In particular, the conditional expectation of the vector of random effects $\underline{\upsilon} = (\underline{\tau}, \underline{\xi})$ given the sample information has the form

$$\hat{\underline{\upsilon}} = \mathrm{E}(\underline{\upsilon} | \underline{y}, \underline{x}; \theta) = \frac{\int_{\mathbb{R}^{N+T}} \underline{\upsilon}\; h(\underline{y}, \underline{\upsilon} | \underline{x}; \theta) d\underline{\upsilon}}{\int_{\mathbb{R}^{N+T}} h(\underline{y}, \underline{\upsilon} | \underline{x}; \theta) d\underline{\upsilon}}, \tag{35}$$

where h denotes the joint conditional pdf of $\underline{y}$ and $\underline{\upsilon}$ given $\underline{x}$ which is given by the integrand of the likelihood function (27).

5 Empirical Results

The ML estimate of the pooled probit model (1) under the assumption that the errors are independent across time and countries are presented in Table 2. The results for the static model ($\kappa = 0$) are reported in the left columns and those of the dynamic specification including the lagged dependent in the right columns.

The parameter estimates 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). 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 makes it non significant. This suggests that government expenditures might capture some omitted serial dependence under the static specification. The coefficient 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 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 four coefficients are statistically significant.

The inclusion of the lagged current account reversal variable substantially improves the fit of the model as indicated by the highly 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. This suggests that a current account reversal significantly increases the probability of a further reversal the following year.

Table 3 reports the estimates of the Butler-Moffitt model (1) and (2), which includes random country specific effects, leading to equicorrelated errors across time periods. 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 Butler-Moffitt 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, this evidence in favor of the random effect specification is not overwhelming. Actually, the coefficients of the explanatory variables and of the lagged dependent state are similar (after adjusting for the different normalization rules) under both specifications.

The estimated probit model with random effects assumes that τ_i is independent of x_{it}. If this were not correct, the parameter estimates would be inconsistent. In order to check this assumption we ran the following auxiliary regression:

$$\hat{\tau}_i = \psi_0 + \bar{x}'_{i\cdot}\psi_1 + \zeta_i, \qquad i = 1, ..., n, \tag{36}$$

where the vector $\bar{x}_{i\cdot}$ contains the mean values of the x_{it}-variables (except for the US interest rate and the OECD growth rate) over time. The value of the F-statistic for the null $\psi_1 = 0$ is 1.85 with critical values of 2.03 and 1.73 for the 5%

and 10% significance levels. Whence, evidence that τ_i might be correlated with $\bar{x}_{i\cdot}$ is inconclusive.

We now turn to the ML estimates of the dynamic random effect model with serially correlated idiosyncratic errors as specified by Equations (1) and (3). This allows for a third source of serial dependence in addition to state dependence and time-invariant unobserved heterogeneity. The ML-EIS estimation results based on $S = 100$ EIS draws and three EIS (fixed-point) iterations are given in the left columns of Table 4. The MC (numerical) standard deviations are computed from 20 ML-EIS estimations under i.i.d. sets of CRNs. They are much smaller than the corresponding asymptotic (statistical) standard deviations indicating that the ML-EIS results are numerically very accurate.

The estimation results indicate that the inclusion of a transitory idiosyncratic error component has significant effects on the dynamic structure of the model but not on the other coefficients which remain quantitatively close to those of the Butler-Moffitt specification. The persistence parameter estimate of ρ equal 0.4 and is statistically significant at the 1% level. Furthermore, the estimated coefficient κ associated with the lagged dependent variable is now substantially smaller and not significantly different from zero. This suggests that the state dependence found under the pooled probit and the Butler-Moffitt model is spurious and the result of an improper dynamic specification of the error term (see Heckman 1981a). Since the parameter σ_τ governing the time-invariant heterogeneity is also not statistically significant, the only source of serial dependence which is relevant for current account crises appears to be the transitory country-specific differences. Note that while the coefficient of ρ is significant at the 1% level, the corresponding LR-statistic equals 2.57 and is not significant. Such discrepancy suggests that the lagged dependent variable in the Butler-Moffitt model acts as a proxy for serial idiosyncratic correlation. The values of the F-statistic for the independence test of τ_i from $\bar{x}_{i\cdot}$ indicate that we can not reject the null of independence at a 10% confidence level.

For the purpose of comparison, the random effect model with serially correlated errors is re-estimated using the standard GHK simulator based on the same simulation sample size as used for EIS ($S = 100$). The results, which are summarized in the right columns of Table 4, reveal that the parameter estimates obtained using GHK exhibit significantly larger MC standard errors than those obtained under EIS. Moreover, while the parameter estimates for the explanatory variables are generally similar for both procedures, the estimates of the parameters governing the dynamics of current account reversals (κ, σ_τ, ρ) are noticeably different. In particular, the ML-GHK estimates of σ_τ and ρ are smaller than their ML-EIS counterparts, while that of κ is larger. This is fully in line with the results of the MC study of Lee (1997) indicating that the ML-GHK estimator exhibits a downward bias for the persistence parameter of the idiosyncratic error as well as for the variation parameter of the unobserved heterogeneity while it is upward biased for the parameter governing the state dependence.

We now turn to the estimation results of the panel model (1), (4), and (5), allowing for unobserved random effects in both dimensions which are summarized in Table 5. The ML-EIS estimation was performed with a simulation sample size of $S = 100$ and three EIS iterations. The MC standard errors reported illustrate how efficiently EIS approximates the $T + N$ integral in Equation (27). The variance parameter of the time factor and its autoregressive parameter are both significant, indicating that there are significant common dynamic time-specific effects. This empirical result, which is in line with IMF concerns (Fisher, 1998) and with several theoretical models (Corsetti et al., 1999), suggests the existence of contagion effects among developing countries. The values of the F-statistic for the independence test indicate that there is no evidence for correlation, neither between the time effects ξ_t and $\bar{x}_{\cdot t}$, where $\bar{x}_{\cdot t}$ contains the mean values of the explanatory variables across countries, nor between the country effects τ_i and $\bar{x}_{i\cdot}$ (see Equation 36).

Furthermore, note that the state-dependence coefficient κ is statistically significant, while the country-specific random effect is again not significantly different from zero. Hence, under the model with time-specific effects the lagged dependent variable seems to act (similar as under the Butler-Moffitt model) as a proxy for *positive* serial *idiosyncratic* correlation. Notice that the serial correlation associated with the factor ξ_t is *negative* and is *common* to all countries. A comparison between the model with serially correlated idiosyncratic errors (Table 4) and that allowing random effects in both dimensions (Table 5) reveals that both are virtually observationally equivalent with very similar coefficients for all explanatory variables in x_{it}.

All in all, we find under all dynamic panel models significant serial correlation characterizing the dynamics of current account crises. Furthermore, there is no evidence for persistent unobserved heterogeneity across country as a possible source for serial dependence. Finally, the data do not allow to discriminate cleary between serially correlated idiosyncratic errors, state dependence and/or dynamic spill over effects as potential sources of serial dependence.

6 Conclusion

This paper uses different non-linear panel data specifications 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: a country-specific random effect, a serially correlated transitory error component, dynamic spill over effects, and a state dependence component to control for the effect of previous events of current account reversal.

For likelihood-based estimation of panel models with country-specific random heterogeneity and serially correlated error components we propose to use Efficient Importance Sampling (EIS) which represents a Monte Carlo (MC) integration technique. The application of EIS allows for numerically very accurate and reliable ML estimation of those models. In particular, it improves significantly the numerical efficiency of GHK, which is the most frequently used MC procedure to estimate non-linear panel models with serially correlated errors.

Our empirical results show that the static pooled probit model is unable to capture the dynamic patterns of the data and that the inclusion of the lagged dependent variable significantly increases the fit of the model. In turn, that variable appears to be only a proxy for an autoregressive error structure capturing transitory unobserved differences across countries. ML-EIS estimation of a panel probit with unobserved individual heterogeneity and autocorrelated idiosyncratic errors finds that the autocorrelation coefficient of the error term is statistically significant, while both the lagged dependent and the country-specific random effect are not. Finally, the ML-EIS estimate of a panel probit model with unobserved individual heterogeneity, as well as a correlated time-specific effects reveals that the time-specific effects indicative of contagion effects among developing countries are siginificant. We found, however, that the model with unobserved individual heterogeneity and serially correlated idiosyncratic errors and that with random country-specific and correlated time-effects are virtually observationally equivalent with very similar coefficients for all explanatory variables.

The empirical results of both models suggest that 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.

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Appendix 1: EIS-implementation for random country-specific effects and serially correlated errors

This appendix details the implementation of the EIS procedure for the panel probit model (1) and (3) to obtain MC estimates for the likelihood contribution $I(\theta)$ given by equation (8). In order to take full advantage of the properties of gaussian kernels, we adopt the following conventions:

(i) Gaussian kernels are represented under their natural parametrization – see Lehmann (1986, section 2.7). Whence, $k_t(\underline{\lambda}_t; a_t)$ in Equation (19) is parameterized as

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

with $D_t^* = (-\infty \ , \ \gamma_t + \delta_t \lambda_0]$. The EIS parameter a_t consists of the six lower diagonal elements of P_t and the three elements in q_t (the positivity constraint on P_t never binds in our application).

(ii) All factorizations of k_t are based upon the Cholesky decomposition of P_t into

$$P_t = L_t \Delta_t L_t', \tag{A-2}$$

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

$$l_{1,t} = (l_{21,t}, l_{31,t})', \quad l_{2,t} = (1, l_{32,t})'. \tag{A-3}$$

The key steps in our EIS implementation consists of finding the analytical expression of $\chi_t(\underline{\eta}_{t-1}; a_t)$. It is the object of the following lemma.

Lemma 1. *The integral of $k_t(\underline{\lambda}_t; a_t)$, as defined in (A-1), w.r.t. ϵ_t is of the form given by Equation (23) together with*

$$k_{2,t}(\underline{\eta}_{t-1}; \cdot) = \exp\left\{ -\frac{1}{2}(d_{2,t}\underline{\eta}_{t-1}' l_{2,t} l_{2,t}' \underline{\eta}_{t-1} + 2\underline{\eta}_{t-1}' l_{2,t} m_{2,t}) \right\} \tag{A-4}$$

$$k_{3,t}(\lambda_0; \cdot) = \exp\left\{ -\frac{1}{2}(d_{3,t}\lambda_0^2 + 2m_{3,t}\lambda_0) \right\} \cdot r_t \tag{A-5}$$

$$\alpha_t = \sqrt{d_{1,t}}\left(\gamma_t + \frac{m_{1,t}}{d_{1,t}}\right), \qquad \beta_t = \sqrt{d_{1,t}}(l_{1,t} + \delta_t \iota) \tag{A-6}$$

$$r_t = \frac{1}{\sqrt{d_{1,t}}} \exp\left\{ \frac{1}{2}\frac{m_{1,t}^2}{d_{1,t}} \right\}, \tag{A-7}$$

with

$$m_t = \{m_{i,t}\} = L_t^{-1} q_t, \quad \iota' = (0, 1). \tag{A-8}$$

Proof. The proof is straightforward under the Cholesky factorization introduced in (A-2), deleting the index t for the ease of notation. First we introduce the transformation $z = L'\underline{\lambda}$, whereby

$$z_1 = \epsilon + l_1'\underline{\eta}_{-1}, \quad z_2 = l_2'\underline{\eta}_{-1}, \quad z_3 = \lambda_0.$$

Whence,

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

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

$$v = \sqrt{d_1}\left(z_1 + \frac{m_1}{d_1}\right).$$

The result immediately follows.□

Next, we provide the full details of the recursive EIS implementation in Equations (12) to (17).

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

$$P_T = e_\rho e_\rho' \quad \text{and} \quad q_T = 0, \tag{A-9}$$

with

$$e_\rho' = (1, -\rho, 0).$$

· *Period* t $(T > t > 1)$: Given Equation (23) together with lemma 1, the product $\varphi_t \cdot \chi_{t+1}$ comprises the following factors: φ_t as defined in Equation (9), $k_{2,t+1}$ as given by Equation (A-4) and $\Phi(\alpha_{t+1} + \beta'_{t+1}\underline{\eta}_t)$, where $(\alpha_{t+1}, \beta_{t+1})$ are defined in Equation (A-6). 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, $k_{0,t}$ in Equation (18) is defined as

$$k_{0,t}(\underline{\lambda}_t; a_t) = k_{2,t+1}(\underline{\eta}_t, \cdot) \exp\left\{-\frac{1}{2}\left[a_{1,t}(\beta'_{t+1}\underline{\eta}_t)^2 + 2a_{2,t}(\beta'_{t+1}\underline{\eta}_t)\right]\right\}, \tag{A-10}$$

with $a_t = (a_{1,t}, a_{2,t})$. It follows that $k_{2,t+1}$ also cancels out in the auxiliary EIS regressions 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 this EIS regressions one obtains estimated values for $(a_{1,t}, a_{2,t})$. Note that $\underline{\eta}_t$ can be written as

$$\underline{\eta}_t = A\underline{\lambda}_t, \quad \text{with} \quad A = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{A-11}$$

It follows that the parameters of the EIS kernel k_t in Equation (A-1) are given by

$$P_t = e_\rho e'_\rho + d_{2,t+1}A'l_{2,t+1}l'_{2,t+1}A + a_{1,t}A'\beta_{t+1}\beta'_{t+1}A \tag{A-12}$$

$$q_t = A'l_{2,t+1}m_{2,t+1} + a_{2,t}A'\beta_{t+1}. \tag{A-13}$$

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

· *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

$$\underline{\lambda}_1 = \underline{\eta}_1 = (\epsilon_1, \lambda_0)', \quad \lambda_0 = \eta_0 \ (= \tau). \tag{A-14}$$

This amounts to replacing A by I_2 in Equations (A-11) to (A-13). Whence, the kernel $k_1(\lambda_1, a_1)$ needs only be bivariate with

$$\begin{aligned} P_1 &= e_1 e_1' + d_{2,2} l_{2,2} l_{2,2}' + \hat{a}_{1,1} \beta_2 \beta_2' && \text{(A-15)} \\ q_1 &= l_{2,2} m_{2,2} + \hat{a}_{2,1} \beta_2, && \text{(A-16)} \end{aligned}$$

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

$$L_1 = \begin{pmatrix} 1 & 0 \\ l_{31,1} & 1 \end{pmatrix}, \quad D_1 = \begin{pmatrix} d_{1,1} & 0 \\ 0 & d_{3,1} \end{pmatrix}, \quad l_{1,1} = l_{31,1}, \tag{A-17}$$

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

$$\beta_1 = \sqrt{d_{1,1}}(l_{1,1} + \delta_1). \tag{A-18}$$

· *Period* $t = 0$ (untruncated integral w.r.t. $\lambda_0 \equiv \tau$): Accounting for the back transfer of $\{k_{3,t}(\lambda_0; \cdot)\}_{t=1}^{T}$, all of which are gaussian kernels, the λ_0-kernel is given by

$$k_0(\lambda_0; \cdot) = f_\tau(\lambda_0) \cdot \prod_{t=1}^{T} k_{3,t}(\lambda_0; \cdot) \cdot \exp\left\{-\frac{1}{2}\left(\hat{a}_{1,0}\lambda_0^2 + 2\hat{a}_{2,0}\lambda_0\right)\right\}, \tag{A-19}$$

where $(\hat{a}_{1,0}, \hat{a}_{2,0})$ are the (fixed point) 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-19).

As mentioned above, fixed point convergence of the EIS auxiliary regressions (17) as well as continuity of corresponding likelihood estimates require the use of CRNs. In order to draw the ϵ_t's from their (truncated) gaussian samplers $m_t(\epsilon_t|\underline{\tilde{\eta}}_{t-1}; \hat{a}_t)$ based on CRNs one can use the following result: If ϵ follows a truncated $\mathrm{N}(\mu, \sigma^2)$ distribution with $b_l < \epsilon < b_u$, then a ϵ-draw is obtained as (see, e.g., Train, 2003)

$$\tilde{\epsilon} = \mu + \sigma\Phi^{-1}\left[\Phi\left(\frac{b_l - \mu}{\sigma}\right) + \tilde{u}\cdot\left\{\Phi\left(\frac{b_u - \mu}{\sigma}\right) - \Phi\left(\frac{b_l - \mu}{\sigma}\right)\right\}\right], \qquad \text{(A-20)}$$

where $\tilde{u}$ is a canonical draw from the $\mathrm{U}(0, 1)$ distribution which is independent from the parameters indexing the distribution of ϵ.

Appendix 2: MC experiments on the numerical efficiency of EIS

In order to compare the numerical accuracy of EIS relative to GHK, we evaluated the integral in Equation (8) under 18 artificial data sets considering three different values of ρ (0.2, 0.5, 0.9), two different values of σ_τ (0.1, 0.5) and three different sample sizes (T=10, 20, 50). All other coefficients are set equal to zero.

For each of these eighteen data sets, we produced 200 i.i.d MC estimates of I_i based upon different sets of CRNs. Both GHK and EIS individual estimates are based upon $S = 200$ auxiliary draws and the number of EIS iterations is fixed at three. In Table A1 we report the means, MC standard deviations and coefficients of variation of the 200 replications under both methods for the eighteen scenarios. As discussed in Richard and Zhang (2007), these standard deviations provide direct measures of numerical accuracy. Note immediately that the MC standard deviation under EIS are systematically lower than those under GHK, by factors ranging from 7 to 315.

As expected numerical accuracy is a decreasing function of ρ, σ_τ and T. This is especially the case for GHK with coefficient of variations above 1 for $T = 50$ and $\rho = 0.9$. In sharp contrast, the worse case scenario for EIS ($T = 50$, $\rho = 0.9$, $\sigma_\tau = 0.5$) has a coefficient of variation of 0.017. A more extensive and detailed MC comparison of GHK and EIS belongs to our research agenda.

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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 the pooled probit model

	Static Model		Dynamic Model	
Variable	Estimate	Asy. s.e.	Estimate	Asy. s.e.
Constant	-1.993^{***}	0.474	-1.955^{***}	0.493
AVGCA	-0.060^{***}	0.012	-0.060^{***}	0.012
AVGGROW	0.008	0.021	0.009	0.021
AVGINV	−0.002	0.010	0.001	0.011
AVGTT	−0.108	0.066	−0.109	0.069
GOV	0.026^{**}	0.012	0.018	0.012
OT	−0.011	0.010	−0.011	0.010
OPEN	−0.058	0.087	−0.085	0.090
USINT	0.108	0.073	0.107	0.075
GROWOECD	0.084	0.086	0.042	0.090
INTPAY	0.024	0.029	0.021	0.030
RES	-0.074^{**}	0.030	-0.074^{**}	0.030
CONCDEB	-0.165^{**}	0.068	-0.152^{**}	0.071
κ			0.981^{***}	0.158
Log-likelihood	−276.13		−257.26	

Note: The estimated model is given by Equation (1) assuming that the errors are independent across countries and time. The asymptotic standard errors are calculated as the square root of the diagonal elements of the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level.

Table 3. ML-estimates of the dynamic Butler-Moffitt random effect model

Variable	Estimate	Asy. s.e.
Constant	-1.880^{***}	0.534
AVGCA	-0.064^{***}	0.015
AVGGROW	0.010	0.021
AVGINV	-0.0001	0.011
AVGTT	-0.122	0.084
GOV	0.018	0.012
OT	-0.011	0.011
OPEN	-0.069	0.093
USINT	0.083	0.075
GROWOECD	0.073	0.090
INTPAY	0.014	0.031
RES	-0.073^{**}	0.035
CONCDEB	-0.159^{**}	0.078
κ	0.982^{***}	0.154
σ_τ	0.162	0.210
σ_e	1.013	
Log-likelihood	-254.47	
LR-statistic for $H_0 : \sigma_\tau = 0$	5.57	
F-statistic for exogeneity	1.85	

Note: The estimated model is given by Equation (1) and (2). The ML-estimation is based on a Gauss-Hermite quadrature using 20 nodes. The asymptotic standard errors are calculated as the square root of the diagonal elements of the inverse Hessian. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1% and 5% percent critical values of the LR-statistic for $H_0 : \sigma_\tau = 0$ are 5.41 and 2.71. The 1% and 5% percent critical values of the F-statistic for exogeneity are 2.71 and 2.03.

Table 4. ML-estimates of the dynamic random effect model with serially correlated idiosyncratic errors

	ML-EIS			ML-GHK		
Variable	Est.	Asy. s.e.	MC s.e.	Est.	Asy. s.e.	MC s.e.
Constant	-1.623^{***}	0.224	0.0074	-1.752^{***}	0.526	0.1015
AVGCA	-0.077^{***}	0.018	0.0006	-0.074^{***}	0.017	0.0028
AVGGROW	0.006	0.028	0.0003	0.007	0.026	0.0009
AVGINV	0.004	0.016	0.0003	0.004	0.015	0.0012
AVGTT	-0.189^{*}	0.103	0.0030	-0.171^{*}	0.094	0.0170
GOV	0.017	0.016	0.0001	0.018	0.015	0.0006
OT	-0.010	0.014	> 0.0001	-0.010	0.013	0.0007
OPEN	-0.123	0.122	0.0029	-0.116	0.118	0.0164
USINT	0.093	0.082	0.0009	0.098	0.082	0.0074
GROWOECD	0.052	0.096	0.0011	0.054	0.093	0.0070
INTPAY	0.031	0.040	0.0007	0.030	0.038	0.0037
RES	-0.109^{**}	0.047	0.0018	-0.103^{**}	0.047	0.0100
CONCDEB	-0.210^{**}	0.080	0.0024	-0.199^{**}	0.093	0.0152
κ	0.440	0.284	0.0173	0.486^{*}	0.259	0.0764
σ_τ	0.199	0.794	0.0048	0.078^{*}	0.051	1.9035
δ	0.404^{***}	0.150	0.0136	0.376^{**}	0.175	0.0615
σ_e	1.111			1.082		
Log-likelihood	-253.19		0.0356	-253.20		0.3356
LR-stat. for $H_0: \rho = 0$	2.57			2.55		
F-stat. for exogeneity	1.32					

Note: The estimated model is given by Equation (1) and (3). The ML-EIS and ML-GHK estimation are based on a MC sample size of $S = 100$. The EIS simulator is based on three EIS iterations. The asymptotic standard errors are calculated as the square root of the diagonal elements of the inverse Hessian and the MC standard errors from 20 replications of the ML-EIS and ML-GHK estimation. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1% and 5% percent critical values of the LR-statistic for $H_0: \rho = 0$ are 6.03 and 3.84. The 1% and 5% percent critical values of the F-statistic for exogeneity are 2.71 and 2.03.

Table 5. ML-estimates of the dynamic model with random country-specific and time effects

Variable	Estimate	Asy. s.e.	MC. s.e.
Constant	-1.967^{***}	0.677	0.0008
AVGCA	-0.064^{***}	0.014	0.0001
AVGGROW	0.013	0.022	> 0.0001
AVGINV	-0.001	0.011	> 0.0001
AVGTT	-0.122	0.075	0.0005
GOV	0.018	0.012	> 0.0001
OT	-0.010	0.011	> 0.0001
OPEN	-0.065	0.095	0.0002
USINT	0.070	0.071	0.0002
GROWOECD	0.113	0.097	0.0001
INTPAY	0.011	0.032	> 0.0001
RES	-0.073^{**}	0.035	0.0002
CONCDEB	-0.163^{**}	0.074	0.0003
κ	1.013^{***}	0.139	0.0004
σ_τ	0.154	0.201	0.0028
δ	-0.888^{***}	0.041	0.0003
σ_ξ	0.089^{**}	0.048	0.0002
σ_e	1.030		
Log-likelihood	-253.1287		0.0052
F-stat. for exogeneity (τ_i)	0.86		
F-stat. for exogeneity (ξ_t)	0.51		

Note: The estimated model is given by Equation (1), (4), and (5). The ML-EIS estimation is based on a MC sample size of $S = 100$ and three EIS iterations. The asymptotic standard errors are calculated as the square root of the diagonal elements of the inverse Hessian and the MC standard errors from 20 replications of the ML-EIS estimation. *,**, and *** indicates statistical significance at the 10%, 5% and 1% significance level. The 1% and 5% percent critical values of the F-statistic for exogeneity in the regression for τ_i are given by 2.71 and 2.03 and in the regression for ξ_t by 7.72 and 4.00, respectively.

Table A1. Monte Carlo simulation results of GHK and EIS

		$\rho = 0.2$		$\rho = 0.5$		$\rho = 0.9$	
		EIS	GHK	EIS	GHK	EIS	GHK
				$T = 10$			
$\sigma_\tau = 0.1$	mean	9.8e-04	9.8e-04	1.9e-03	1.9e-03	4.7e-03	4.7e-03
	std. dev.	1.7e-07	1.9e-05	4.5e-06	1.0e-04	1.9e-05	5.3e-04
	coeff. var.	1.7e-04	2.0e-02	2.4e-03	5.5e-02	4.2e-03	1.1e-01
$\sigma_\tau = 0.5$	mean	7.9e-04	7.9e-04	5.5e-03	5.4e-03	1.4e-01	1.4e-01
	std. dev.	5.4e-07	3.6e-05	2.4e-05	3.4e-04	1.5e-03	9.8e-03
	coeff. var.	6.9e-04	4.5e-02	4.3e-03	6.3e-02	1.1e-02	7.0e-02
				$T = 20$			
$\sigma_\tau = 0.1$	mean	6.9e-07	6.9e-07	1.0e-06	9.7e-07	6.7e-06	5.9e-06
	std. dev.	1.4e-10	2.2e-08	3.1e-09	8.8e-08	7.7e-08	1.5e-06
	coeff. var.	2.0e-04	3.1e-02	3.0e-03	9.0e-02	1.2e-02	2.6e-01
$\sigma_\tau = 0.5$	mean	7.8e-07	7.7e-07	2.6e-06	2.5e-06	8.3e-06	6.6e-06
	std. dev.	6.5e-10	4.6e-08	1.5e-08	2.7e-07	1.1e-07	1.6e-06
	coeff. var.	8.3e-04	6.0e-02	6.0e-03	1.0e-01	1.4e-02	2.4e-01
				$T = 50$			
$\sigma_\tau = 0.1$	mean	1.4e-15	1.4e-15	1.1e-14	1.0e-14	7.6e-10	8.3e-10
	std. dev.	2.9e-19	9.2e-17	3.9e-17	2.3e-15	1.1e-11	9.7e-10
	coeff. var.	2.0e-04	6.4e-02	3.5e-03	2.2e-01	1.5e-02	1.2e+00
$\sigma_\tau = 0.5$	mean	3.5e-15	3.5e-15	4.8e-15	4.8e-15	1.1e-09	1.3e-09
	std. dev.	2.3e-18	4.0e-16	1.8e-17	1.6e-15	1.8e-11	1.8e-09
	coeff. var.	6.6e-04	1.1e-01	3.7e-03	3.4e-01	1.7e-02	1.4e+00

Note: MC-estimation of the likelihood contribution I_i under the panel model (1) and (3) for a simulated fictitious sample $\{y_{it}\}_{t=1}^{T}$ (see Equation 8). The mean, the standard deviation and the coefficient of variation are obtained from 200 independent replications of the MC estimation of I_i. The EIS and GHK MC-estimates are based upon a simulation sample size $S = 200$.