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International Investment Positions and Exchange Rate Dynamics

Michael Binder
Christian J. Offermanns

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Michael Binder†

Goethe University Frankfurt

Christian J. Offermanns‡

Freie Universität Berlin

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Abstract

We revisit medium- to long-run exchange rate determination, focusing on the role of international investment positions. To do so, we make use of a new econometric framework accounting for conditional long-run homogeneity in heterogeneous dynamic panel data models. In particular, in our model the long-run relationship between effective exchange rates and domestic as well as weighted foreign prices is a homogeneous function of a country's international investment position. We find rather strong support for purchasing power parity in environments of limited negative net foreign asset to GDP positions; furthermore, long-run exchange rate equilibria may have little relation to purchasing power parity outside such environments. We thus argue that the purchasing power parity hypothesis holds conditionally, but not unconditionally, and that international investment positions are an essential component to characterizing this conditionality.

Keywords: Exchange Rate Determination; International Financial Integration; Dynamic Panel Data Models.

JEL Classification: F31; F37; C23.

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†E-mail: mbinder@wiwi.uni-frankfurt.de

‡E-mail: christian.offermanns@fu-berlin.de

1 Introduction

Research on exchange rate dynamics constitutes a continued cornerstone of applied economic investigations. A sizeable fraction of these investigations have aimed at understanding the driving forces of medium- to long-run exchange rate dynamics. Nevertheless, little consensus has been reached. In particular, in the quest to characterize medium- to long-run anchors for the fluctuations of exchange rates, the purchasing power parity (PPP) hypothesis has received support by some studies, yet has been rejected by others. While these differences in empirical findings may in part be attributed to choice of econometric methodology, the differences have also emerged due to different currency pairs and/or different time periods being considered.

For research in this area to move forward, it thus appears essential to view the PPP hypothesis as (at most) conditionally valid and to pay close consideration to the interaction between exchange rate fluctuations on the one hand and the macroeconomic as well as financial environment within which the pricing of currencies occurs on the other hand. One important aspect of the financial globalization we have witnessed over the last few decades has been the dynamics of countries' net international investment positions, resulting in the emergence of heightened external imbalances. In this paper, we study the interaction between medium- to long-run exchange rate dynamics and a country's net international investment position. We analyze to what extent the PPP hypothesis may be viewed as an anchor for the pricing of a currency over medium- to long-run horizons *if conditioned* on the net international investment position of the country issuing the currency.

Previous work on the PPP hypothesis (for example, Taylor, Peel and Sarno, 2001), has argued that mean reversion of real exchange rates only occurs under sufficiently large misalignments relative to PPP. For such dynamics of exchange rates their pricing would, however, need to adhere to PPP unconditionally, at least in the long run. In this paper, we in contrast conjecture that foreign exchange market participants consider PPP to be an appropriate measure for medium- to long-run exchange rate pricing only if they perceive that key macroeconomic and financial indicators are in imbalance. Our starting point for characterizing such imbalances in the macroeconomic and financial environment that are relevant for exchange rate pricing is the net foreign asset (NFA) to GDP ratio as a measure of a country's net international investment position. We investigate the hypothesis that if foreign exchange market participants perceive this investment position to be imbalanced of such magnitude that exchange rate adjustment both appears called for and would seem to make a difference in bringing the investment position back into balance, that the market participants then expect a return of exchange rates to a fundamental anchor, and that this fundamental anchor is given by the PPP relationship. We also investigate the hypothesis that under rather severe imbalances in a country's international investment position foreign exchange market participants may doubt that reversion of exchange rates towards PPP constitutes a key to the necessary adjustment process, and that therefore, as in the absence of imbalances, market participants pay little – if any – attention to PPP as a relevant anchor even for medium- to long-run exchange rate determination.

We test these hypotheses in this paper and more generally provide a characterization of the role of international investment positions for medium- to long-run exchange rate dynamics using a panel of up to 72 countries over the time period 1970 to 2004. We propose and implement a new dynamic panel data model for our analysis. Our panel model has a variety of appealing features: In line with existing state of the art cross-country panel models in the literature, our model explicitly distinguishes between short- and long-run dynamics, does not impose untenable exogeneity restrictions, is valid in the presence of unit roots in the series being considered, and allows for heterogeneous short-run dynamics of these series across countries. It moves beyond the models presently available in the panel data literature by introducing *conditional* homogeneity across countries in the long-run relation between the series. We model the conditional long-run homogeneity both parametrically using flexible functional form polynomials (resulting in what we call the conditional pooled mean group (CPMG) panel model) and non-parametrically using local kernels (resulting in what we call the state kernel mean group (SKMG) panel model). We believe that this econometric framework could indeed be appealing for a wide range of panel data sets with sufficiently large time dimension for which traditional pooling restrictions are not tenable.

Our main empirical results are as follows: We find rather strong support for the PPP hypothesis in environments of limited negative international investment positions as measured by the NFA to GDP ratio. In such environments the coefficients in the long-run relation between effective nominal exchange rates, domestic prices and weighted foreign prices are (economically) close to their predicted values under PPP. Furthermore, the speed of adjustment towards the long-run relation is, in light of the estimates typically obtained in the previous literature, surprisingly fast, at less than two years half-life of shocks to the PPP relation. We also document that in environments of large negative and zero NFA to GDP positions the PPP hypothesis does not provide a relevant medium- to long-run anchor for the pricing of currencies. Our robustness analysis finds that qualitatively our results are not driven by a variety of other features of the macroeconomic and financial environment. While there is some quantitative sensitivity of the range of NFA to GDP positions for which the PPP hypothesis appears valid to a country's income level, its degree of price stability and the volatility of its terms of trade shocks (though not its exchange rate regime), the conditioning of PPP on a country's international investment position remains important under variations in these factors.

The remainder of this paper is organized as follows: In Section 2 we discuss the relation of our work to previous literature, both that on medium- to long-run exchange rate dynamics and that on cross-country panel models. Section 3 develops the CPMG and SKMG panel models. We outline the main features of the database on international capital flows and international investment positions that we have assembled and work with in this paper in Section 4. Our empirical findings are presented in Section 5, and Section 6 concludes and discusses directions for future research. Three appendices provide details on various aspects of inference in the CPMG and SKMG models.

2 Relation to the Literature

2.1 Exchange Rate Dynamics

While there is an enormous body of literature investigating the validity of the purchasing power parity hypothesis,[1] rather limited attention has been paid to investigating the interaction between exchange rate dynamics and the macroeconomic as well as financial environment within which the pricing of currencies occurs. Three of the exceptions are Cheung and Lai (2000), Taylor, Peel and Sarno (2001) and Binder, Pesaran and Sharma (2004). Taylor, Peel and Sarno (2001) propose a nonlinear model for medium- to long-run real exchange rate dynamics, capturing that mean reversion of real exchange rates would only occur if real exchange rates deviated sufficiently strongly from the PPP anchor. Cheung and Lai (2000) and Binder, Pesaran and Sharma (2004) – using different types of dynamic panel models involving simple sample splits – argue that the empirical validity of the PPP hypothesis is linked to the volatility of domestic prices, and that below a minimum threshold of price volatility arbitrage opportunities would be too small for PPP to hold.

None of these papers considers the link between exchange rate determination and a country's international investment position. Theoretical bases for this link were discussed inter alia by Dornbusch and Fischer (1980) and by Cavallo and Ghironi (2002); the latter make the case for a dependence of exchange rates on net foreign assets both under a model with flexible and with sticky prices. Gourinchas and Rey (2007) argue that valuation effects represent an important part of the dynamics of investment positions and exchange rates. Other important papers empirically investigating the link between exchange rate determination and a country's international investment position include Faruqee (1995), Gagnon (1996), Lane and Milesi-Ferretti (2004) and Cheung, Chinn and Pascual (2005). All of these latter empirical papers consider a linear regression specification with the real exchange rate as the dependent variable and a measure of the international investment position as one of

[1]For a recent review of the PPP literature see, for example, Taylor and Taylor (2004). Engel, Mark and West (2007) discuss state of the art exchange rate modelling beyond the PPP literature also.

the regressors. Our approach, in contrast, will *not* be to add the international investment position as an additional regressor, implying unconditional rejection of the PPP hypothesis if this regressor is significant and unconditional support for the PPP hypothesis if this regressor is insignificant. We follow an alternative approach to evaluating PPP as considered in the literature for example by Krugman (1978); this approach involves estimating the coefficients in the (long-run) relation between the nominal exchange rate, domestic prices and foreign prices and inspecting how closely the estimated coefficients correspond to the values predicted by PPP. We allow the relevant coefficients to continuously vary across different macroeconomic environments, particularly across different degrees of imbalance in a country's international investment position. We are thus able to investigate the hypothesis that if a country's international investment position is imbalanced of such magnitude that exchange rate adjustment both appears called for and would seem to make a difference in bringing the investment position back into balance, that then foreign exchange market participants expect macroeconomic fundamentals to matter, and that these fundamentals can be described by one of the simplest no-arbitrage relations there is, namely PPP. We will also investigate the hypothesis that imbalances from a certain magnitude onwards may be too severe for foreign exchange market participants to still expect that a PPP-based reversion to fundamentals would occur. Clearly, investigation of these hypotheses requires specification of a nonlinear empirical model, though the nonlinearity has quite different economic underpinnings than in Taylor, Peel and Sarno (2001). We think that our dynamic model with *conditionally* homogeneous long-run relations is a more informative means to characterize the link between a country's international investment position and its medium- to long-run exchange rate dynamics than the default linear regression approach of tacking on the international investment position as an additional regressor – for the reasons that our model allows for bands of real exchange rate reversion (as well as lack thereof), is able to characterize the economic determinants of these bands and does not impose a monotonic relationship between changes in a country's international investment position and its exchange rate adjustment.

2.2 Panel Data and Varying Parameter Models

Key to the understanding of the recent econometric literature on cross-country dynamic panel data models is the result by Pesaran and Smith (1995) that if a model's slope coefficients vary across countries, whether randomly or systematically, that then the means of the coefficients cannot be estimated consistently using a model imposing cross-country homogeneity of the slope coefficients (and only allowing for structural heterogeneity in the form of random or fixed effects). To obtain consistent estimators of the means of the slope coefficients, Pesaran and Smith (1995) proposed the mean group (MG) estimator based on the idea of averaging the estimates obtained from country-specific time-series regressions. This MG estimator has the drawback of not materializing any of the efficiency gains that are feasible when some economic features are common across countries. While macroeconomic short-run dynamics beyond some common shocks are rather unlikely to share common features across a broad range of countries, common features often may be present in long-run relationships. This insight is exploited by the pooled mean group (PMG) estimator of Pesaran, Shin and Smith (1999), which imposes homogeneity of the slope coefficients entering the long-run relationships, but allows for unrestricted heterogeneity of the coefficients characterizing the short-run dynamics.

The dynamic panel model we propose in this paper addresses situations where the homogeneity of the slope coefficients entering the long-run relationships does not hold unconditionally, but rather is tied to certain features of the macroeconomic and financial environment. In such settings, the PMG estimator would yield inconsistent estimates of the long-run slope coefficients, while the MG estimator would still suffer from lack of efficiency. We will pursue two approaches to modelling the dependence of the long-run slope coefficients on features of the macroeconomic and financial environment. Our first approach is parametric, modelling the state dependence using flexible functional form polynomials to reflect that economic theory may provide limited insight into the functional form of the interrelation between the long-run slope coefficients on the one hand and the macroeconomic and financial environment on the other hand. Our second approach involves modelling the state dependence via non-parametric kernel methods. The statistical literature on non-parametric varying parameter models in static regression settings on which our modelling approach builds is quite extensive; see, for example, Fan and Zhang (1999). Kumar and Ullah (2000) have employed a related non-parametric approach in the context of a univariate dynamic panel model studying convergence of cross-country output growth, though their conditioning is not linked to any features of the macroeconomic and financial environment.

3 Econometric Methodology

3.1 The Mean Group and Pooled Mean Group Panel Models

We begin by reviewing the dynamic panel models, mean group (MG) and pooled mean group (PMG), on which our proposed new panel modelling framework does build. Let us consider the heterogeneous panel version of an autoregressive distributed lag, ARDL(p,q), model in error-correction representation:

$$\Delta y_{it} = \omega_i + \alpha_i y_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{x}_{i,t-1} + \sum_{k=1}^{p-1} \phi_{ik} \Delta y_{i,t-k} + \sum_{k=0}^{q-1} \boldsymbol{\delta}_{ik}' \Delta \boldsymbol{x}_{i,t-k} + u_{it}, \tag{1}$$

where $i = 1, 2, \ldots, N$ indexes countries, $t = 1, 2, \ldots, T$ indexes time periods, Δ denotes the difference operator, y_{it} represents the dependent variable, $\boldsymbol{x}_{it}$ represents the $(m \times 1)$ vector of explanatory variables, ϕ_{ik} and $\boldsymbol{\delta}_{ik}$ denote coefficient scalars and vectors of corresponding dimension, and ω_i represents the country-specific intercept term (fixed effect). We assume that T is sufficiently large so that the ARDL model in (1) can be estimated for each country separately. Note that for notational convenience, we neglect any subscripts to both, the time dimension T and the lag orders p and q. In the empirical application of this model we nevertheless allow for an unbalanced panel as well as for lag orders that vary across variables and cross-section units; the modifications to the model's equations should be straightforward.

The error term u_{it} is assumed to be distributed independently across time, although it does not necessarily have to be uncorrelated across i. In particular, we allow for such cross-section dependence through the following common factor structure:

$$u_{it} = \boldsymbol{\lambda}_i' \boldsymbol{f}_t + \varepsilon_{it}, \tag{2}$$

such that the source of error term dependencies across countries is captured by the common factors $\boldsymbol{f}_t$, whereas the impacts of these factors on each country are governed by the idiosyncratic loadings in $\boldsymbol{\lambda}_i$. The error component ε_{it} is assumed to be distributed independently across i and t with zero mean and variance $\sigma_i^2 > 0$.

Although the common factors in $\boldsymbol{f}_t$ are modelled as unobservable, we can control for these by augmenting the model (1) with cross-sectional averages of the model's observable variables following the correlated effects augmentation (CEA) of Pesaran (2006). Averaging (1) across i under the assumption that slope coefficients and regressors are uncorrelated, one obtains

$$\Delta \bar{y}_t = \bar{\omega} + \bar{\alpha} \bar{y}_{t-1} + \bar{\boldsymbol{\beta}}' \bar{\boldsymbol{x}}_{t-1} + \sum_{k=1}^{p-1} \bar{\phi}_k \Delta \bar{y}_{t-k} + \sum_{k=0}^{q-1} \bar{\boldsymbol{\delta}}_k' \Delta \bar{\boldsymbol{x}}_{t-k} + \bar{\boldsymbol{\lambda}}' \boldsymbol{f}_t + \bar{\varepsilon}_t, \tag{3}$$

where $\bar{y}_{t-k} = N^{-1} \sum_{i=1}^N y_{i,t-k}$, $\bar{\phi}_k = N^{-1} \sum_{i=1}^N \phi_{ik}$, $k = 0, 1, ..., p$; $\bar{\boldsymbol{x}}_{t-k} = N^{-1} \sum_{i=1}^N \boldsymbol{x}_{i,t-k}$, $\bar{\boldsymbol{\delta}}_k = N^{-1} \sum_{i=1}^N \boldsymbol{\delta}_{ik}$, $k = 0, 1, ..., q$; $\bar{\omega} = N^{-1} \sum_{i=1}^N \omega_i$, $\bar{\alpha} = N^{-1} \sum_{i=1}^N \alpha_i$, $\bar{\boldsymbol{\beta}} = N^{-1} \sum_{i=1}^N \boldsymbol{\beta}_i$, $\bar{\boldsymbol{\lambda}} = N^{-1} \sum_{i=1}^N \boldsymbol{\lambda}_i$ and $\bar{\varepsilon}_t = N^{-1} \sum_{i=1}^N \varepsilon_{it}$. Since the error component ε_{it} by assumption is distributed independently across i and t, $\bar{\varepsilon}_t$ tends to zero in root mean square error as N becomes large. The cross-sectional correlation in u_{it} can therefore be captured through a linear combination of the cross-sectional averages of the dependent variable and of all regressors:

$$\boldsymbol{\lambda}_i' \boldsymbol{f}_t = \vartheta_i \bar{\boldsymbol{\lambda}}' \boldsymbol{f}_t = \eta_i \bar{y}_{t-1} + \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}_{t-1} + \sum_{k=0}^{p-1} \nu_{ik} \Delta \bar{y}_{t-k} + \sum_{k=0}^{q-1} \boldsymbol{\varsigma}_{ik}' \Delta \bar{\boldsymbol{x}}_{t-k} - \vartheta_i \bar{\omega}, \tag{4}$$

with $\eta_i = -\vartheta_i \bar{\alpha}$, $\boldsymbol{\zeta}_i = -\vartheta_i \bar{\boldsymbol{\beta}}$, $\nu_{i0} = \vartheta_i$, $\nu_{ik} = -\vartheta_i \bar{\phi}_k$, $k = 1, 2, ..., p-1$, and $\boldsymbol{\varsigma}_{ik} = -\vartheta_i \bar{\boldsymbol{\delta}}_k$, $k = 0, 1, ..., q-1$, for some ϑ_i.

Using Equation (4), the CEA representation of the model (1) and (2) can be written as:

$$\begin{aligned}\Delta y_{it} = \mu_i + \alpha_i y_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{x}_{i,t-1} + \sum_{k=1}^{p-1} \phi_{ik} \Delta y_{i,t-k} + \sum_{k=0}^{q-1} \boldsymbol{\delta}_{ik}' \Delta \boldsymbol{x}_{i,t-k} \\ + \eta_i \bar{y}_{t-1} + \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}_{t-1} + \sum_{k=0}^{p-1} \nu_{ik} \Delta \bar{y}_{t-k} + \sum_{k=0}^{q-1} \boldsymbol{\varsigma}_{ik}' \Delta \bar{\boldsymbol{x}}_{t-k} + \varepsilon_{it},\end{aligned} \tag{5}$$

with $\mu_i = \omega_i - \vartheta_i \bar{\omega}$.

From (5), the long-run relationship between y and $\boldsymbol{x}$ is given by

$$y_i^{LR} = -\alpha_i^{-1} \boldsymbol{\beta}_i' \boldsymbol{x}_i^{LR} - \alpha_i^{-1} \mu_i - \alpha_i^{-1} \eta_i \bar{y}^{LR} - \alpha_i^{-1} \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}^{LR} = \boldsymbol{\theta}_i' \boldsymbol{x}_i^{LR} + \varpi_i + \rho_i \bar{y}^{LR} + \boldsymbol{\varrho}_i' \bar{\boldsymbol{x}}^{LR} \tag{6}$$

where the superscript LR denotes the long-run value of the respective variable.

In what follows, we will focus our attention on a part of the coefficients that constitute the key coefficients of economic interest, i.e. the speed of adjustment parameter α_i and the long-run coefficients $\boldsymbol{\theta}_i$. Hence, let us collect the remaining coefficients and regressors,

$$\begin{aligned}\boldsymbol{\psi}_i = (\mu_i \;\; \phi_{i1} \;\; \phi_{i2} \;\; \dots \;\; \phi_{i,p-1} \;\; \boldsymbol{\delta}_{i0}' \;\; \boldsymbol{\delta}_{i1}' \;\; \dots \;\; \boldsymbol{\delta}_{i,q-1}' \\ \eta_i \;\; \boldsymbol{\zeta}_i' \;\; \nu_{i0} \;\; \nu_{i1} \;\; \dots \;\; \nu_{i,p-1} \;\; \boldsymbol{\varsigma}_{i0}' \;\; \boldsymbol{\varsigma}_{i1}' \;\; \dots \;\; \boldsymbol{\varsigma}_{i,q-1}')'\end{aligned}$$

and

$$\begin{aligned}\boldsymbol{h}_{it} = (1 \;\; \Delta y_{i,t-1} \;\; \Delta y_{i,t-2} \;\; \dots \;\; \Delta y_{i,t-p+1} \;\; \Delta \boldsymbol{x}_{it}' \;\; \Delta \boldsymbol{x}_{i,t-1}' \;\; \dots \;\; \Delta \boldsymbol{x}_{i,t-q+1}' \\ \bar{y}_{t-1} \;\; \bar{\boldsymbol{x}}_{\boldsymbol{t-1}}{}' \;\; \Delta \bar{y}_t \;\; \Delta \bar{y}_{t-1} \;\; \dots \;\; \Delta \bar{y}_{t-p+1} \;\; \Delta \bar{\boldsymbol{x}}_t' \;\; \Delta \bar{\boldsymbol{x}}_{t-1}' \;\; \dots \;\; \Delta \bar{\boldsymbol{x}}_{t-q+1}')',\end{aligned}$$

to obtain a compact version of (5),

$$\Delta y_{it} = \alpha_i y_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}_i' \boldsymbol{h}_{it} + \varepsilon_{it}. \tag{7}$$

The Pesaran and Smith (1995) MG estimators of α_i and $\boldsymbol{\theta}_i$ are obtained by least-squares estimation of (7) for each country separately, computing $\hat{\boldsymbol{\theta}}_i = -\hat{\alpha}_i^{-1} \hat{\boldsymbol{\beta}}_i$ and subsequently averaging the country-specific coefficient estimates. Standard errors for these MG estimates can be computed non-parametrically on the basis of the spread of the coefficients across countries.

The idea underlying the Pesaran, Shin and Smith (1999) PMG estimation is to assume that the long-run coefficients $\boldsymbol{\theta}_i$ are homogeneous across all countries, that is, $\boldsymbol{\theta}_i = -\hat{\alpha}_i^{-1} \hat{\boldsymbol{\beta}}_i \equiv \boldsymbol{\theta},\ i = 1, 2, ..., N$, in Equation (7), whereas all other coefficients are still allowed to differ in unrestricted fashion across countries, leading to the following model:

$$\Delta y_{it} = \alpha_i (y_{i,t-1} - \boldsymbol{\theta}' \boldsymbol{x}_{i,t-1}) + \boldsymbol{\psi}_i' \boldsymbol{h}_{it} + \varepsilon_{it}. \tag{8}$$

Since (8) is nonlinear in $\boldsymbol{\theta}$, the PMG estimator is usually based on numerical maximization of the implied likelihood function.

3.2 Conditioning the Dynamic Panel Model

The PMG estimator exhibits considerable appeal for the study of exchange rate dynamics: It is rather unlikely that the *short-run* dynamics of nominal exchange rates and domestic as well as foreign prices exhibit strong commonalities across countries – it thus appears to be a very sensible choice to let such short-run dynamics differ in unconstrained fashion across countries, as the PMG estimator does do. At the same time, the PPP hypothesis imposes a common restriction across countries on the *long-run* coefficients, that the PMG estimator does incorporate.

As we have argued in the Introduction, though, it seems unlikely that PPP would hold even in the long run across all countries and their differing macroeconomic and financial environments. To capture the interaction between medium- to long-run exchange rate dynamics on the one hand and a country's international investment position on the other hand, we propose to condition the coefficients in the long-run relation between nominal exchange rates and domestic as well as foreign prices on a predetermined state variable measuring a country's international investment position. To map this idea back to the generic panel error-correction model (8), denoting the value of the conditioning predetermined state variable by $z_{i,t-1}$,[2] we therefore propose the following augmented model:

$$\Delta y_{it} = \alpha_i(z_{i,t-1})[y_{i,t-1} - \boldsymbol{\theta}(z_{i,t-1})'\boldsymbol{x}_{i,t-1}] + \boldsymbol{\psi}_i(z_{i,t-1})'\boldsymbol{h}_{it} + \varepsilon_{it} \tag{9}$$

Note that this specification corresponds to the PMG approach of Pesaran, Shin and Smith (1999): all short-run coefficients in (9) are a function of both, $z_{i,t-1}$ as well as other country-specific characteristics (reflected in the i subscripts for all coefficient functionals), but the long-run coefficients in (9) are specified across all countries as homogeneous functions of the conditioning variable.

3.2.1 Parametric Conditioning: The Conditional Pooled Mean Group Model

For what we will call the conditional pooled mean group (CPMG) model, we propose to specify $\boldsymbol{\theta}(z_{i,t-1})$ using a parametric function of flexible form, and in particular choose Chebyshev polynomials as one specification of orthogonal polynomials.[3] Our CPMG model thus specifies that

$$\boldsymbol{\theta}(z_{i,t-1}) = \sum_{s=0}^{\tau} \boldsymbol{\gamma}_s^{(\boldsymbol{\theta})} \cdot c_s(z_{i,t-1}), \tag{10}$$

[2] In this paper, we specify $z_{i,t-1}$ to be a scalar. The extension to considering a vector of state variables is beyond the scope of this paper and is left for future research.

[3] We work with orthogonal polynomials in part as an effective means to avoid multicollinearity problems.

with the Chebyshev polynomials $c_s(z_{i,t-1})$ recursively defined as

$$c_{s+1}(z_{i,t-1}) = 2z_{i,t-1}c_s(z_{i,t-1}) - c_{s-1}(z_{i,t-1}), \quad s = 1, 2, ..., \tau,$$

initialized as $c_0(z_{i,t-1}) = 1$ and $c_1(z_{i,t-1}) = z_{i,t-1}$, and where $\boldsymbol{\gamma}_s^{(\boldsymbol{\theta})}$ is an m-dimensional vector of coefficients that is homogeneous across countries. The coefficient functionals $\alpha_i(z_{i,t-1})$ and $\boldsymbol{\psi}_i(z_{i,t-1})$ can be specified in similar form (albeit with country-specific rather than homogeneous coefficients).

We stack the variables and coefficients along the time dimension, noting that the coefficients are time-specific

$$\Delta \boldsymbol{y}_i = \boldsymbol{\alpha}_i(\boldsymbol{z}_{i,-1}) \odot \left[\boldsymbol{y}_{i,-1} - \sum_{\ell=1}^{m} \boldsymbol{\theta}_\ell(\boldsymbol{z}_{i,-1}) \odot \boldsymbol{x}_{\ell,i,-1} \right] + \sum_{\ell=1}^{n} \boldsymbol{\psi}_{\ell,i}(\boldsymbol{z}_{i,-1}) \odot \boldsymbol{h}_{\ell,i} + \boldsymbol{\varepsilon}_i, \tag{11}$$

where $\Delta \boldsymbol{y}_i = [\Delta y_{i1} \ \Delta y_{i2} \ \dots \ \Delta y_{i,T}]'$, $\boldsymbol{\alpha}_i(\boldsymbol{z}_{i,-1}) = [\alpha_i(z_{i0}) \, \alpha_i(z_{i1}) \ \dots \ \alpha_i(z_{i,T-1})]'$, $\boldsymbol{y}_{i,-1} = [y_{i0} \ y_{i1} \ \dots \ y_{i,T-1}]'$, $\boldsymbol{\theta}_\ell(\boldsymbol{z}_{i,-1}) = [\theta_\ell(z_{i0}) \, \theta_\ell(z_{i1}) \ \dots \ \theta_\ell(z_{i,T-1})]'$, $\boldsymbol{x}_{\ell,i,-1} = (x_{\ell,i,0} \ x_{\ell,i,1} \ \dots \ x_{\ell,i,T-1})'$, $\ell = 1, 2, ..., m$, $\boldsymbol{\psi}_{\ell,i}(\boldsymbol{z}_{i,-1}) = [\psi_{\ell i}(z_{i0}) \, \psi_{\ell i}(z_{i1}) \ \dots \ \psi_{\ell i}(z_{i,T-1})]'$, $\boldsymbol{h}_{\ell,i} = (h_{\ell,i,1} \ h_{\ell,i,2} \ \dots \ h_{\ell,i,T})'$, $\ell = 1, 2, ..., n$, $n = 2p + 1 + m(2q + 1)$, and $\boldsymbol{\varepsilon}_i = [\varepsilon_{i1} \ \varepsilon_{i2} \ \dots \ \varepsilon_{i,T}]'$. The symbol $\odot$ denotes element-wise multiplication of vectors.

One approach to the estimation of the CPMG model is to concentrate the likelihood function, writing it as a function of $\alpha_i(z_{i,t-1})$ and $\boldsymbol{\theta}(z_{i,t-1})$ (the coefficient functions of economic interest) only, and subsequently maximize this concentrated likelihood function. A computationally less burdensome alternative that we follow here is to adapt the two-step generalized least-squares (GLS) estimation strategy proposed by Breitung (2005) for the PMG model to our CPMG model. We rewrite (11) in a form which is linear in the coefficients like in the initial setup of Equation (7),

$$\Delta \boldsymbol{y}_i = \boldsymbol{\alpha}_i(\boldsymbol{z}_{i,-1}) \odot \boldsymbol{y}_{i,-1} + \sum_{\ell=1}^{m} \boldsymbol{\beta}_{\ell,i}(\boldsymbol{z}_{i,-1}) \odot \boldsymbol{x}_{\ell,i,-1} + \sum_{\ell=1}^{n} \boldsymbol{\psi}_{\ell,i}(\boldsymbol{z}_{i,-1}) \odot \boldsymbol{h}_{\ell,i} + \boldsymbol{\varepsilon}_i, \tag{12}$$

where $\boldsymbol{\beta}_{\ell,i}(\boldsymbol{z}_{i,-1}) = [\beta_{\ell i}(z_{i0}) \, \beta_{\ell i}(z_{i1}) \ \dots \ \beta_{\ell i}(z_{i,T-1})]'$, $\ell = 1, 2, \dots, m$. In order to circumvent element-wise multiplication and use standard matrix algebra instead, we can diagonalize the data vectors and rewrite the coefficients as linear functions of the polynomial parameters

$$\begin{aligned}
\Delta \boldsymbol{y}_i &= \mathrm{diag}(\boldsymbol{y}_{i,-1})\boldsymbol{\alpha}_i(\boldsymbol{z}_{i,-1}) + \sum_{\ell=1}^{m} \mathrm{diag}(\boldsymbol{x}_{\ell,i,-1})\boldsymbol{\beta}_{\ell,i}(\boldsymbol{z}_{i,-1}) + \sum_{\ell=1}^{n} \mathrm{diag}(\boldsymbol{h}_{\ell,i})\boldsymbol{\psi}_{\ell,i}(\boldsymbol{z}_{i,-1}) + \boldsymbol{\varepsilon}_i \\
&= \mathrm{diag}(\boldsymbol{y}_{i,-1})\boldsymbol{\Pi}_{\tau_\alpha}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\alpha_i)} + \sum_{\ell=1}^{m} \mathrm{diag}(\boldsymbol{x}_{\ell,i,-1})\boldsymbol{\Pi}_{\tau_\beta}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\beta_{\ell i})} \\
&\qquad + \sum_{\ell=1}^{n} \mathrm{diag}(\boldsymbol{h}_{\ell,i})\boldsymbol{\Pi}_{\tau_\psi}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\psi_{\ell i})} + \boldsymbol{\varepsilon}_i \\
&= \boldsymbol{\mathcal{Y}}_{\tau_\alpha,i,-1}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\alpha_i)} + \boldsymbol{\mathcal{X}}_{\tau_\beta,i,-1}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\boldsymbol{\beta}_i)} + \boldsymbol{\mathcal{H}}_{\tau_\psi,i}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}_i^{(\boldsymbol{\psi}_i)} + \boldsymbol{\varepsilon}_i,
\end{aligned} \tag{13}$$

where

$$\boldsymbol{\gamma}_i^{(\alpha_i)} = \left[\gamma_{0i}^{(\alpha_i)}\,\gamma_{1i}^{(\alpha_i)}\,\gamma_{2i}^{(\alpha_i)}\;\ldots\;\gamma_{\tau_\alpha i}^{(\alpha_i)}\right]',$$

$$\boldsymbol{\gamma}_i^{(\boldsymbol{\beta}_i)} = \left[\boldsymbol{\gamma}_i^{(\beta_{1i})'}\;\;\boldsymbol{\gamma}_i^{(\beta_{2i})'}\;\;\ldots\;\;\boldsymbol{\gamma}_i^{(\beta_{mi})'}\right]',\;\;\boldsymbol{\gamma}_i^{(\beta_{\ell i})} = \left[\gamma_{0i}^{(\beta_{\ell i})}\,\gamma_{1i}^{(\beta_{\ell i})}\,\gamma_{2i}^{(\beta_{\ell i})}\;\ldots\;\gamma_{\tau_\beta i}^{(\beta_{\ell i})}\right]',$$

$$\boldsymbol{\gamma}_i^{(\boldsymbol{\psi}_i)} = \left[\boldsymbol{\gamma}_i^{(\psi_{1i})'}\;\;\boldsymbol{\gamma}_i^{(\psi_{2i})'}\;\;\ldots\;\;\boldsymbol{\gamma}_i^{(\psi_{ni})'}\right]',\;\;\boldsymbol{\gamma}_i^{(\psi_{\ell i})} = \left[\gamma_{0i}^{(\psi_{\ell i})}\,\gamma_{1i}^{(\psi_{\ell i})}\,\gamma_{2i}^{(\psi_{\ell i})}\;\ldots\;\gamma_{\tau_\psi i}^{(\psi_{\ell i})}\right]',$$

$$\boldsymbol{\mathcal{Y}}_{\tau_\alpha,i,-1}(\boldsymbol{z}_{i,-1}) = \mathrm{diag}(\boldsymbol{y}_{i,-1})\boldsymbol{\Pi}_{\tau_\alpha}(\boldsymbol{z}_{i,-1}),$$

$$\boldsymbol{\mathcal{X}}_{\tau_\beta,i,-1}(\boldsymbol{z}_{i,-1}) = \left[\,\mathrm{diag}(\boldsymbol{x}_{1,i,-1})\boldsymbol{\Pi}_{\tau_\beta}(\boldsymbol{z}_{i,-1})\;\;\mathrm{diag}(\boldsymbol{x}_{2,i,-1})\boldsymbol{\Pi}_{\tau_\beta}(\boldsymbol{z}_{i,-1})\;\;\ldots\;\;\mathrm{diag}(\boldsymbol{x}_{m,i,-1})\boldsymbol{\Pi}_{\tau_\beta}(\boldsymbol{z}_{i,-1})\right],$$

$$\boldsymbol{\mathcal{H}}_{\tau_\psi,i}(\boldsymbol{z}_{i,-1}) = \left[\,\mathrm{diag}(\boldsymbol{h}_{1,i})\boldsymbol{\Pi}_{\tau_\psi}(\boldsymbol{z}_{i,-1})\;\;\mathrm{diag}(\boldsymbol{h}_{2,i})\boldsymbol{\Pi}_{\tau_\psi}(\boldsymbol{z}_{i,-1})\;\;\ldots\;\;\mathrm{diag}(\boldsymbol{h}_{n,i})\boldsymbol{\Pi}_{\tau_\psi}(\boldsymbol{z}_{i,-1})\right]$$

and

$$\boldsymbol{\Pi}_{\tau_\varphi}(\boldsymbol{z}_{i,-1}) = [\boldsymbol{\iota}_T\,c_1(\boldsymbol{z}_{i,-1})\,c_2(\boldsymbol{z}_{i,-1})\;\ldots\;c_{\tau_\varphi}(\boldsymbol{z}_{i,-1})]\text{ with dimension }(T\times\tau_\varphi+1).$$

In the first step we estimate the coefficients in (13) (including σ_i^2) consistently using country-specific least squares. In a second step, we estimate the conditionally homogeneous long-run coefficients through least-squares estimation of a transformed model that has concentrated out all country-specific coefficients, namely,

$$\boldsymbol{v}_i = -\boldsymbol{\mathcal{X}}_{\tau_\theta,i,-1}(\boldsymbol{z}_{i,-1})\boldsymbol{\gamma}^{(\boldsymbol{\theta})} + \boldsymbol{\epsilon}_i, \tag{14}$$

where

$$\boldsymbol{v}_i = \hat{\boldsymbol{A}}_i(\boldsymbol{z}_{i,-1})^{-1}\left[\Delta\boldsymbol{y}_i - \boldsymbol{\mathcal{H}}_{\tau_\psi,i}(\boldsymbol{z}_{i,-1})\hat{\boldsymbol{\gamma}}_i^{(\boldsymbol{\psi}_i)}\right] - \boldsymbol{y}_{i,-1},$$

$$\boldsymbol{\epsilon}_i = \hat{\boldsymbol{A}}_i(\boldsymbol{z}_{i,-1})^{-1}\boldsymbol{\varepsilon}_i, \qquad V(\boldsymbol{\epsilon}_i) = \hat{\boldsymbol{A}}_i(\boldsymbol{z}_{i,-1})^{-2}\hat{\sigma}_i^2,$$

with $\boldsymbol{A}_i(\boldsymbol{z}_{i,-1}) = \mathrm{diag}[\boldsymbol{\alpha}_i(\boldsymbol{z}_{i,-1})]$ and

$$\boldsymbol{\gamma}^{(\boldsymbol{\theta})} = [\boldsymbol{\gamma}^{(\theta_1)'}\,\boldsymbol{\gamma}^{(\theta_2)'}\;\ldots\;\boldsymbol{\gamma}^{(\theta_m)'}]',\;\;\boldsymbol{\gamma}^{(\theta_\ell)} = [\gamma_0^{(\theta_\ell)}\;\gamma_1^{(\theta_\ell)}\;\ldots\;\gamma_{\tau_\theta}^{(\theta_\ell)}]',\;\;\ell = 1,2,\ldots,m.$$

To improve upon the first-step estimates, the resulting coefficient estimates $\hat{\boldsymbol{\gamma}}^{(\boldsymbol{\theta})}$ can be plugged into (11) to re-estimate the first-step parameters. Using these estimates again in (14), the procedure can be conducted iteratively until some convergence criterion is reached.

In practice, to keep the model structure parsimonious one may wish to restrict the polynomial order τ_ψ corresponding to the regressors $\boldsymbol{h}_{it}$ to zero. Note that such a restriction is completely consistent with the idea of unrestricted cross-country heterogeneity of the model's short-run dynamics. Due to the heterogeneous nature of the functional relationship between α_i and the conditioning variable z that still remains under such a restriction, we should be explicit about how we propose to compute a panel estimate of the speed of adjustment coefficient for each value of the conditioning state variable. For each $z_{i,t-1}$, we compute the average across all functionals $\alpha_j(z_{i,t-1})$, $j = 1, 2, ..., N$, incorporating in the averaging procedure a weighting with respect to the local environment for which each $\alpha_j(z_{i,t-1})$ has been estimated. The details of the procedure we use to compute a smoothed mean group (SMG) estimate of the speed of adjustment coefficient and its corresponding standard error are provided in Appendix A.

3.2.2 Non-Parametric Conditioning: The State Kernel Mean Group Model

The CPMG model carefully separates the form of the effect of changes in the conditioning state variable $z_{i,t-1}$ on speed of adjustment/short-run coefficients (through country-specific conditioning functions) from those on the long-run coefficients (through pooled conditioning functions). An alternative conditioning procedure would be to make the form of the conditioning dependent on the specific value that the conditioning state variable assumes; that is, to construct conditioning functions that do not differ across short- vs. long-run coefficients, but for both types of coefficients give priority to "neighboring" values of the conditioning state variable, and assign more distant values of the conditioning state variable a relatively minor role in shaping the conditioning functions.

To pursue this latter idea, our state kernel mean group (SKMG) model introduces a non-parametric kernel approach to the following panel error-correction model:

$$\Delta y_{it} = \alpha(z_{i,t-1})y_{i,t-1} + \boldsymbol{\beta}(z_{i,t-1})'\boldsymbol{x}_{i,t-1} + \boldsymbol{\psi}(z_{i,t-1})'\boldsymbol{h}_{it} + \varepsilon_{it} \tag{15}$$

Note that for such a kernel estimation approach, there is no advantage in taking account of the nonlinearity captured in the model (9) since the coefficient functionals are specified as being locally homogeneous.[4] Hence, for the long-run coefficient we have $\boldsymbol{\theta}(z_{i,t-1}) = -\alpha(z_{i,t-1})^{-1}\boldsymbol{\beta}(z_{i,t-1})$ within a local neighborhood around $z_{i,t-1}$, similar to the MG estimation approach to (7).

To estimate the parameters $\boldsymbol{\varphi}(z_{i,t-1}) = [\alpha(z_{i,t-1})\ \boldsymbol{\beta}(z_{i,t-1})'\ \boldsymbol{\psi}(z_{i,t-1})']'$, building on the work of Kumar and Ullah (2000), we weight all available observations using a kernel function and minimize a modified residual sum of squares, namely

$$\hat{\boldsymbol{\varphi}}(z) = \underset{\boldsymbol{\varphi}(z)}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} \varepsilon_{it}^2\ \kappa_b(z_{i,t-1} - z), \quad \forall z \in \{z_{it}\}_{i=1,2,...,N,\,t=1,2,...,T} \tag{16}$$

where $\kappa_b(z_{i,t-1} - z)$ represents the kernel that effectively gives higher weight to observations $z_{i,t-1}$ that are "close" to z and lower weight to those observations that are "far" from this value, with b denoting the bandwidth parameter that controls this neighborhood. In

[4] Specifying e.g. the speed of adjustment parameter as being locally heterogeneous requires a prohibitively large amount of observations for z around $z_{i,t-1}$ *for each country* i and will usually not be feasible in empirical applications.

particular, we define

$$\kappa_b(z_{i,t-1} - z) = \mathcal{K}\left(\frac{z_{i,t-1} - z}{b}\right),$$

where $\mathcal{K}(\cdot)$ denotes a standard kernel function such as the Gaussian kernel.[5] We follow Pagan and Ullah (1999, p. 26) and choose the bandwidth parameter for the Gaussian kernel as

$$b = 1.06\, s_z\, (NT)^{-1/5},$$

with s_z representing the overall standard deviation of $z_{i,t-1}$, $i = 1, 2, ..., N$, $t = 1, 2, ..., T$.

Taking account of heteroskedastic variances σ_i^2, Equation (16) can be solved using the local least-squares kernel (LLSK) estimator,

$$\hat{\boldsymbol{\varphi}}(z) = [\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(z)\boldsymbol{W}]^{-1}\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(z)\Delta\boldsymbol{y}, \tag{17}$$

where

$$\boldsymbol{W} = (\boldsymbol{y}_{-1}\ \ \boldsymbol{X}_{-1}\ \ \boldsymbol{H}),$$

$$\boldsymbol{\Omega}^{-1}(z) = \boldsymbol{\Omega}^{-1/2}\boldsymbol{K}_b(\boldsymbol{z}_{-1} - z)\boldsymbol{\Omega}^{-1/2},$$

with $\Delta\boldsymbol{y} = (\Delta\boldsymbol{y}_1{}'\ \Delta\boldsymbol{y}_2{}'\ \ldots\ \Delta\boldsymbol{y}_N{}')'$, $\boldsymbol{y}_{-1} = (\boldsymbol{y}_{1,-1}{}'\ \boldsymbol{y}_{2,-1}{}'\ \ldots\ \boldsymbol{y}_{N,-1}{}')'$, $\boldsymbol{X}_{-1} = (\boldsymbol{X}_{1,-1}{}'\ \boldsymbol{X}_{2,-1}{}'\ \ldots\ \boldsymbol{X}_{N,-1}{}')'$ $\boldsymbol{X}_{i,-1} = (\boldsymbol{x}_{i0}\ \boldsymbol{x}_{i1}\ \ldots\ \boldsymbol{x}_{i,T-1})'$, $i = 1, 2, ..., N$ and $\boldsymbol{H} = (\boldsymbol{H}_1{}'\ \boldsymbol{H}_2{}'\ \ldots\ \boldsymbol{H}_N{}')'$. $\boldsymbol{K}_b(\boldsymbol{z}_{-1} - z)$ is a diagonal matrix containing the values of $\kappa_b(z_{i,t-1} - z)$ for $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$:

$$\boldsymbol{K}_b(\boldsymbol{z}_{-1} - z) = \mathrm{diag}\left(\boldsymbol{K}_b(\boldsymbol{z}_{1,-1} - z),\ \boldsymbol{K}_b(\boldsymbol{z}_{2,-1} - z),\ \ldots,\ \boldsymbol{K}_b(\boldsymbol{z}_{N,-1} - z)\right),$$

$$\boldsymbol{K}_b(\boldsymbol{z}_{i,-1} - z) = \mathrm{diag}\left(\kappa_b(z_{i0} - z),\ \kappa_b(z_{i1} - z),\ \ldots,\ \kappa_b(z_{i,T-1} - z)\right).$$

The variance matrix $\boldsymbol{\Omega}$ is defined as

$$\boldsymbol{\Omega} = \mathrm{diag}(\sigma_1^2,\ \sigma_2^2,\ \ldots,\ \sigma_N^2) \otimes \boldsymbol{I}_T,$$

and can be estimated using OLS estimates of σ_i^2 for each country. The variance of the parameter estimates can thus be obtained as

$$V[\hat{\boldsymbol{\varphi}}(z)] = [\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(z)\boldsymbol{W}]^{-1}\boldsymbol{W}'\boldsymbol{\Omega}_1^{-1}(z)\boldsymbol{W}[\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(z)\boldsymbol{W}]^{-1}, \tag{18}$$

where $\boldsymbol{\Omega}_1^{-1}(z) = \boldsymbol{\Omega}^{-1/2}\boldsymbol{K}^2(\boldsymbol{z}_{-1} - z)\boldsymbol{\Omega}^{-1/2}$.

Similar to the parametric CPMG approach, we wish to focus on the relation between the conditioning variable on the one hand and the speed of adjustment and long-run coefficients on the other hand. To that aim, we concentrate out the coefficients of the remaining variables such that in Equations (17) and (18) the matrix $\boldsymbol{W}$ and the vector $\Delta\boldsymbol{y}$ are replaced by

$$\boldsymbol{W}^* = \boldsymbol{M}(\boldsymbol{y}_{-1}\ \boldsymbol{X}_{-1}) \quad \text{and} \quad \Delta\boldsymbol{y}^* = \boldsymbol{M}\Delta\boldsymbol{y}, \tag{19}$$

[5] Note that the specific kernel function is not crucial for the estimation results as for kernels belonging to the same class, the bandwidth parameter can be adjusted using "canonical kernels" such that the estimated functions are largely equivalent (see, e.g. Härdle, 1990).

respectively, to obtain estimates for the concentrated vector of coefficients $\boldsymbol{\varphi}^*(z_{i,t-1}) = [\alpha(z_{i,t-1})\ \boldsymbol{\beta}(z_{i,t-1})']'$, where $\boldsymbol{M} = \text{diag}(\boldsymbol{M}_1,\ \boldsymbol{M}_2,\ ...,\ \boldsymbol{M}_N)$, $\boldsymbol{M}_i = \boldsymbol{I}_T - \boldsymbol{H}_i(\boldsymbol{H}_i'\boldsymbol{H}_i)^{-1}\boldsymbol{H}_i',\ i = 1, 2, ..., N$, with $\boldsymbol{I}_T$ denoting the identity matrix of dimension T and $\boldsymbol{H}_i$ stacking the extracted regressors, $\boldsymbol{H}_i = (\boldsymbol{h}_{i1}\ \ \boldsymbol{h}_{i2}\ \ \dots\ \ \boldsymbol{h}_{iT})'$.

Furthermore, to allow for richer patterns of coefficient variation across values of the conditioning state variable than obtained by the LLSK estimator, for our SKMG model we incorporate, as far as possible, polynomials of higher order into the conditioning procedure as employed in static regression settings by Fan and Zhang (1999). To incorporate the polynomials in the computation of the local coefficients, we again make use of Chebyshev polynomials. We therefore modify the regressors (19) as follows:

$$\tilde{\boldsymbol{W}}(z) = [\tilde{\boldsymbol{w}}_{11}(z)\ \ \tilde{\boldsymbol{w}}_{12}(z)\ \ \dots\ \ \tilde{\boldsymbol{w}}_{NT}(z)]', \tag{20}$$

where

$$\tilde{\boldsymbol{w}}_{it}(z) = [\tilde{\boldsymbol{w}}_{1,it}'(z)\ \ \tilde{\boldsymbol{w}}_{2,it}'(z)\ \ \dots\ \ \tilde{\boldsymbol{w}}_{m+n+1,it}'(z)]' \tag{21}$$

and

$$\begin{aligned}\tilde{\boldsymbol{w}}_{\ell,it}'(z) &= w_{\ell,it}^*\ [c_0(z_{i,t-1}-z)\ \ c_1(z_{i,t-1}-z)\ \ c_2(z_{i,t-1}-z)\ \ \dots\ \ c_\tau(z_{i,t-1}-z)] \\ &= w_{\ell,it}^*\ \boldsymbol{\pi}_\tau(z_{i,t-1}-z)', \quad \ell = 1, 2, \dots, m+n+1. \end{aligned} \tag{22}$$

Note that $w_{\ell,it}^*$ refers to observation (i, t) for the ℓ-th variable in $\boldsymbol{W}^*$. In practice, the order τ will only be small to avoid multicollinearity problems, given that the values of $z_{i,t-1}$ to be included will not vary much since they will be in a small neighborhood around z.

Given that for computational efficiency, we actually compute the estimated coefficients for a grid of equidistant values for z, we denote the (intermediate) estimator for $\tilde{\boldsymbol{\varphi}}^*(z)$ that results from the right-hand side of (17) (with $\boldsymbol{W}$ replaced by $\tilde{\boldsymbol{W}}$ and with $\Delta\boldsymbol{y}$ replaced by $\Delta\boldsymbol{y}^*$) as $\hat{\tilde{\boldsymbol{\varphi}}}^*(z)$, and those of its elements that correspond to the regressors $\tilde{\boldsymbol{w}}_{\ell,it}(z)$ as $\hat{\tilde{\boldsymbol{\varphi}}}_\ell^*(z)$. This estimator can in turn be used to construct final interpolated estimates of $\boldsymbol{\varphi}^*(z)$ at actual observations of the conditioning variable, $\hat{\boldsymbol{\varphi}}^*(z_{i,t-1})$, as

$$\hat{\varphi}_\ell^*(z_{i,t-1}) = \frac{\sum_z \boldsymbol{\pi}_\tau(z - z_{i,t-1})'\hat{\tilde{\boldsymbol{\varphi}}}_\ell^*(z)\kappa_b(z - z_{i,t-1})}{\sum_z \kappa_b(z - z_{i,t-1})}, \quad \ell = 1, 2, \dots, m+n+1, \tag{23}$$

and

$$V[\hat{\varphi}_\ell^*(z_{i,t-1})] = \frac{\sum_z \boldsymbol{\pi}_\tau(z - z_{i,t-1})'V[\hat{\tilde{\boldsymbol{\varphi}}}_\ell^*(z)]\boldsymbol{\pi}_\tau(z - z_{i,t-1})\kappa_b(z - z_{i,t-1})}{\sum_z \kappa_b(z - z_{i,t-1})}, \quad \ell = 1, 2, \dots, m+n+1, \tag{24}$$

where the summation $\sum_z$ runs over the grid of values for z. We call the resultant estimator the SKMG estimator.

Contrasting the ideas underlying the CPMG and SKMG modelling approaches, the parametric CPMG clearly is the more parsimonious of the two approaches. However, it also tends to be the less robust of the two approaches, as the curvatures of the conditioning functions can be more heavily influenced by outlying values of the conditioning variable.[6] All modelling approaches, MG, PMG, CPMG and SKMG, require the existence of a long-run relation between y_{it} and $\boldsymbol{x}_{it}$ which has to be tested for prior to the application of the estimation procedures. Appendix B reviews the panel cointegration test of Westerlund (2005), which we will employ in the empirical part of our paper, and provides reasoning why it may be applied both for models with unconditional and those with conditional long-run relations.

4 International Capital Flow and Investment Position Data

We have assembled a new database for this paper featuring data on international capital flows and the implied international investment positions of countries. Our database comprises these data on an annual basis for a total of 153 countries over the time period 1970 to 2004. We obtained most of the flow data from the International Monetary Fund's (IMF) Balance of Payments Statistics (BOPS); stock data were taken from the IMF's International Investment Position (IIP) database as well as the World Bank's Global Development Finance (GDF) database. All international capital data we used were compiled in millions of U.S. Dollars. In addition to international capital flows and stocks, our database incorporates data on gross domestic product (GDP) from the World Bank's World Development Indicators database,[7] bilateral nominal exchange rates and consumer prices from the IFS, as well as exports and imports which are taken from the Direction of Trade Statistics also maintained by the IMF.

The key difficulty in the compilation of our database was that the IIP for most countries only contains a small number of observations. It was therefore essential to augment the IIP stock data by cumulating flow data. For this cumulation the stock data have to be initialized with an existing stock figure for some reference period. For the overall investment position of a country, the NFA position, possibly the best source of such a figure is Sinn (1990) who provides NFA estimates for up to 145 countries over the period 1970 to 1987. For the subcomponents of NFA we used stock data from the IIP database for purposes of initialization. Given that the flow data may have an earlier starting point than the stock data, occasionally we needed to backcast the initial stock value. In effect, our cumulative flow figures are thus anchored by the first available stock figure from IIP data. We did not compute cumulative flow figures if they did not overlap with corresponding stock data.

[6]A more detailed analysis and comparison of the finite and large sample properties of the CPMG and SKMG estimators is beyond the scope of this paper.

[7]Some of the GDP data in this database are reported in domestic currency values; we converted such GDP data to U.S. Dollar figures using yearly average bilateral exchange rates.

Changes in the stock of any asset or liability are not only due to new flows, but can also be due to changes in the value of the existing stock. The sources of valuation changes differ across types of financial assets and liabilities. In particular, we adjusted portfolio equity investment liabilities using domestic stock market indices adjusted for exchange rate changes (obtained from Datastream that in turn draws upon Morgan Stanley and other sources) and portfolio equity investment assets using a world stock market index (MSCI World Index from Morgan Stanley). Furthermore, we adjusted foreign direct investment (FDI) liabilities using bilateral real exchange rates relative to the United States, and FDI assets using effective real exchange rates.[8] Changes in the value of external debt are already incorporated in the stock values reported in the GDF database, and changes in the value of international reserve assets were obtained from the difference between flows and the change in the corresponding stock value. Denoting net valuation changes aggregated across all asset and liability types as ΔNV, we finally obtained the stock of NFA as

$$NFA_{it} = NFA_{i,t-1} + CA_{it} + KA_{it} + \Delta NV_{it}, \tag{25}$$

where CA_{it} denotes country i's current account balance at time t and KA_{it} refers to its capital account balance.[9]

Since we completed compilation of our database, Lane and Milesi-Ferretti (2007) have augmented the international capital flow and investment position database described in Lane and Milesi-Ferretti (2001); the new version of the Lane and Milesi-Ferretti database now has similar cross-country and time coverage as our database. In contrast to Lane and Milesi-Ferretti (2007), our database also separately reports the valuation effects. So as to be able to assess the role of net valuation changes for our results for exchange rate dynamics using a single database, we prefer to use our database, but we will provide in Section 5 a robustness check of our results using the Lane and Milesi-Ferretti (2007) database. For more details on the construction of our database, see Offermanns and Pramor (2007).

[8] Throughout this paper we use effective exchange rates computed using trade weights. Denoting by e_{ijt} the nominal spot exchange rate between country i and country j (units of country i currency per unit of country j currency), measured as annual averages, we compute the effective exchange rate as $e_{it} = \sum_{j=1}^{N} \tilde{w}_{ijt} e_{ijt}$. The weights $\tilde{w}_{ijt}$ are computed as predetermined moving averages of country i's trade volume with country j as a share of country i's overall trade volume, that is $\tilde{w}_{ijt} = 1/r \cdot \sum_{s=t-r}^{t-1} w_{ijs}$ with $w_{ijt} = (EXP_{ijt} + IMP_{ijt})/(\sum_{k=1}^{N} EXP_{ikt} + IMP_{ikt})$, where EXP_{ijt} and IMP_{ijt} denote country i's exports to and imports from country j in U.S. Dollars, and the window width is chosen as $r = 3$. While a mixture of trade and capital weights might be most appealing, we have to restrict our attention to trade weights, as information on *bilateral* flows of capital that would be needed to compute informative capital weights at present is not available for (even a substantial sub-sample of) the broad cross section of countries we wish to examine.

[9] According to the definitions laid out in the fifth edition of the Balance of Payments Manual (BOPM), the sum of the current account balance and the capital account balance offset what is called the financial account balance. Some of the literature still refers to what the BOPM labels as the capital account balance as "net capital transfers" (within the current account), reserving the term "capital account balance" for the change in NFA that we are aiming at.

While our overall database contains annual observations on a total of 153 countries, for the empirical analysis of this paper we restrict attention to 65 countries only. These countries were selected from the 153 countries in our database on the basis of the following criteria:

(i) at least 25 consecutive time-series observations available for all variables entering our analysis;

(ii) population size of at least one million in 1970;[10]

(iii) economy not centrally planned for (most of) the sample period (according to the classification used by Hall and Jones, 1999);

(iv) economy not a major oil producer (according to the classification used by Mankiw, Romer and Weil, 1992).

The resultant 65 countries included in our analysis are: Argentina, Australia, Austria, Bolivia, Brazil, Burkina Faso, Canada, Chile, Colombia, Costa Rica, Côte d'Ivoire, Denmark, Dominican Republic, Ecuador, Egypt, Finland, France, Germany, Ghana, Guatemala, Haiti, Honduras, India, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea, Libya, Madagascar, Malaysia, Mexico, Morocco, Myanmar, Netherlands, New Zealand, Nigeria, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, El Salvador, Senegal, Sierra Leone, Singapore, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syrian Arab Republic, Thailand, Togo, Turkey, Uganda, United Kingdom, United States, Uruguay and Venezuela.[11]

Over our sample period, the process of international financial integration has had a significant impact on countries' net international investment positions, namely has led to a marked increase of imbalances in net international investment positions. As one measure, the cross-country dispersion of the NFA to GDP ratio has increased by 84% over our sample period (see Figure 1). As we wish to examine to what extent imbalances in a country's international investment position induce corrections towards PPP as a foreign exchange market anchor, in what follows we will focus on these net, not gross, international investment positions.[12] While an analysis of the sources of the marked increase in net international investment position imbalances might need to cope with structural changes, for example due to capital account liberalization, for the purposes of our analysis – namely investigating the interrelation between a country's net international investment position and its medium- to long-run exchange rate determination – we can arguably view the rising cross-country dispersion of

[10]The population data were taken from the World Bank's World Development Indicators, complemented by data from the Penn World Tables.

[11]For our robustness check using the Lane and Milesi-Ferretti (2007) database, using the same criteria as under (i) to (iv), we can include seven more countries in the analysis. The additional countries are: Algeria, Belgium, Cameroon, Greece, Indonesia, Irland, Malawi and Niger, while in turn Sierra Leone is not included in the sample any more.

[12]Figure 1 confirms the well-documented "world NFA discrepancy" (see, for example, Lane and Milesi-Ferretti, 2007) with a ratio of aggregate NFA to aggregate GDP that averages at -0.058 over our sample period. For the full data set of 153 countries in our database, the ratio of aggregate NFA to aggregate GDP averages at -0.048 over our sample period.

the NFA to GDP ratio merely as helpful to ensure sufficient spread in the net international investment position as the conditioning model variable.

5 Empirical Analysis

5.1 Model Specification

To facilitate discussion of our empirical results, let us adapt the generic notation used in Section 3 for our panel ARDL model to the exchange rate model that we take to the data. Based on our general panel error-correction model (9) we specify:

$$\begin{aligned}\Delta e_{it} = \mu_i + \alpha_i(\tilde{z}_{i,t-1}) \left[e_{i,t-1} - \boldsymbol{\theta}_i(\tilde{z}_{i,t-1})' \begin{pmatrix} p_{i,t-1} \\ p^*_{i,t-1} \end{pmatrix} \right] + \eta_i \bar{e}_{t-1} + \zeta_{1i}\bar{p}_{t-1} + \zeta_{2i}\bar{p}^*_{t-1} \\ + \sum_{k=1}^{p_i-1} \phi_{ik}\Delta e_{i,t-k} + \sum_{k=0}^{q_{1i}-1} \delta_{1ik}\Delta p_{i,t-k} + \sum_{k=0}^{q_{2i}-1} \delta_{2ik}\Delta p^*_{i,t-k} \\ + \sum_{k=0}^{p_i-1} \nu_{ik}\Delta \bar{e}_{t-k} + \sum_{k=0}^{q_{1i}-1} \varsigma_{1ik}\Delta \bar{p}_{t-k} + \sum_{k=0}^{q_{2i}-1} \varsigma_{2ik}\Delta \bar{p}^*_{t-k} + \varepsilon_{it}, \end{aligned} \tag{26}$$

where e_{it} denotes the logarithm of country i's effective nominal spot exchange rate, p_{it} the logarithm of country i's consumer price index and p^*_{it} the logarithm of weighted foreign consumer price indices (using the same weighting scheme as for the effective exchange rate)[13]. The variable $\tilde{z}_{it}$ denotes a smooth function of the NFA to GDP ratio over the preceding years in the sample as a measure for the past medium- to long-run trend of the country's international investment position that is cleansed of short-run volatility (details regarding the smoothing procedure will be presented below).

Note that the PPP hypothesis does not pin down a unique choice of dependent and independent variables for the ARDL model. We specify the effective nominal exchange rate as the dependent variable, as our primary interest is in how the nominal and real exchange rates adjust to changes of macroeconomic and financial fundamentals. Our choice of the dependent variable does not imply that we are assuming domestic and weighted foreign prices to be (strictly) exogenous, however. In the context of ARDL models endogeneity of an independent variable can be overcome by adding sufficiently many lags of that independent variable.[14] To account for the presence of global shocks, following our discussion in Section 3 we augment the model by incorporating cross-sectional averages of the observable variables, denoted by $\bar{e}_t$, $\bar{p}_t$ and $\bar{p}^*_t$, respectively.

[13]As is well known, the use of aggregate price indices implies that the long-run relationship, even if consistent with the PPP hypothesis, can only be interpreted as providing evidence for relative (but not absolute) PPP.

[14]For a more detailed discussion of this issue in the time-series setting see Pesaran and Shin (1999).

The parameters of principal interest are those that have immediate structural interpretation, namely the long-run coefficients $\boldsymbol{\theta}_i(\tilde{z}_{i,t-1}) = [\theta_{1i}(\tilde{z}_{i,t-1}),\, \theta_{2i}(\tilde{z}_{i,t-1})]'$ and the speed of adjustment parameter $\alpha_i(\tilde{z}_{i,t-1})$. Note that (unconditional) PPP implies that $\theta_{1i} = 1$ and $\theta_{2i} = -1$ with $\alpha_i < 0$. By conditioning these coefficients on $\tilde{z}_{i,t-1}$, we render them dependent on the country's smoothed NFA to GDP ratio. Specifically, the filter we use is a one-sided version of the Hodrick and Prescott (1997) filter that uses only the preceding ω observations for calculating the estimate of the medium- to long-run component $\tilde{z}_{i,t-1}$ for all t, also ensuring that the conditioning variable can be treated as predetermined.

Given that empirical results could be sensitive to the specification of the width of the window of observations ω used to separate short- from medium-/long-run dynamics, we implement several alternative choices for this parameter varying between $\omega = 3, 5, 7$ and 10 years. These choices are intended to reflect a significant range of foreign exchange market participants' views as regards to the relevant horizon of international investment position data to condition on. For the beginning of the sample, to avoid losing a significant number of observations we compute the initial values of the $\{\tilde{z}_{i,t-1}\}$ series using the average change of the actual NFA to GDP ratio over the initialization period, $t = 1, 2, ..., \omega$.

We have considered a number of other specifications of z_{it} than the NFA to GDP ratio also, including cumulative current account balances and changes in asset and liability valuation (all scaled by GDP). Interestingly, changes in asset and liability valuation seemed an ineffective conditioning variable, whereas the results we will report in what follows were nearly unchanged when we used the unadjusted cumulative current account balance. In contrast to the findings of Gourinchas and Rey (2007), this suggests that valuation effects as a component of the international investment position are not the major driving force of the adjustment of effective exchange rates to macroeconomic fundamentals. While beyond the scope of this paper, it would be interesting to explore in future research what is driving these differences in results relative to Gourinchas and Rey (2007).

In the next section, we will present our results, using the trend component in the NFA to GDP ratio as the conditioning variable, comparing the different estimation approaches discussed in Section 3. For MG estimation of our model, we specify $\alpha_i(\tilde{z}_{i,t-1}) = \alpha_i$ and $\boldsymbol{\theta}_i(\tilde{z}_{i,t-1}) = \boldsymbol{\theta}_i$. For PMG estimation, we specify $\alpha_i(\tilde{z}_{i,t-1}) = \alpha_i$ and $\boldsymbol{\theta}_i(\tilde{z}_{i,t-1}) = \boldsymbol{\theta}$. For CPMG estimation, we specify $\boldsymbol{\theta}_i(\tilde{z}_{i,t-1}) = \boldsymbol{\theta}(\tilde{z}_{i,t-1})$, with $\alpha_i(\tilde{z}_{i,t-1})$ and $\boldsymbol{\theta}(\tilde{z}_{i,t-1})$ modelled as first- and third-order Chebyshev polynomials, respectively. For SKMG estimation, we use a Gaussian kernel combined with homogeneous coefficient first-order Chebyshev polynomials to model the state dependence of α_i and $\boldsymbol{\theta}_i$. Lag orders are selected on the basis of the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC).

5.2 Empirical Results

5.2.1 Testing the Model Specification

We begin by examining the stationarity properties of the various variables entering our model for exchange rate dynamics (26). For this model to be well specified, the model variables should be either integrated of order zero or one, I(0) or I(1), and the long-run levels relation between the model variables should be I(0). To test for the order of integration of nominal effective exchange rates, e, domestic prices, p, and weighted foreign prices, p^*, we employ the panel unit root test of Pesaran (2007).[15] The results in Table 1(a) provide strong evidence that p and p^* are I(1) variables. Somewhat surprisingly, the evidence in favor of e to be I(1) is less compelling. However, as the unit root test statistic for the level of e was insignificant at the one percent level when the cross-sectional augmentation term was dropped, we proceed with the consensus view in the literature that e is best modelled as I(1). We invoke the test statistic proposed by Westerlund (2005) to test for (conditional) panel cointegration between e, p and p^*, that is, the existence of an I(0) relation between e, p and p^* depending on our conditioning variable $\tilde{z}$; Appendix B provides details on the test statistic and its applicability for our panel modelling approach. Table 1(b) provides evidence that $e - \theta_1(\tilde{z})p - \theta_2(\tilde{z})p^*$ is I(0). The results in Table 1(b) are based on a third-order Chebyshev polynomial specification of $\boldsymbol{\theta}(\tilde{z})$, but we obtained qualitatively similar results when we reduced the polynomial order to zero or one. Overall, Table 1 provides strong support for the exchange rate model in Equation (26) being an appropriate model formulation concerning (non-)stationarity of the model variables.

Non-stationarity of exchange rates and price indices on the individual country level implies potential non-stationarity also in the cross-sectional averages of these variables. In principle, the inclusion of common effects being I(1) does not pose a problem to the estimation approach, see Kapetanios, Pesaran and Yamagata (2011). However, the correlated effects augmentation is introduced to capture cross-sectional correlation between error terms which is stationary by its very nature. Furthermore, we are interested in interpreting the relation between the individual country levels of our variables as (conditional) long-run equilibria such that the stochastic trends should not be extracted by the common factor approximation. Hence, in our empirical specification we incorporate only the stationary components of the correlated effects, using the decomposition according to Beveridge and Nelson (1981).

[15] This panel unit root test *inter alia* allows for two features of the data that are accounted for in the model in Equation (26) also: country-specific short-run dynamics and cross-country correlation of the disturbance terms.

5.2.2 Estimation Results for the Full Sample

We can thus turn to estimation results for the coefficients with structural interpretation in our exchange rate model in Equation (26). Table 2 reports the long-run coefficients on p and p^* in the long-run relation between effective nominal exchange rates, domestic prices and weighted foreign prices, as well as the speed of adjustment to this long-run relation under the different estimation procedures we consider. The first two columns report MG and PMG estimation results, whereas the third and fourth columns show the average estimates across all values of the conditioning variable, the smoothed NFA to GDP ratio, obtained under CPMG and SKMG. In contrast to the MG estimates that do not involve any form of pooling, the estimates of both long-run parameters based on all other estimation procedures are highly significant. It may be worth pointing out that the standard errors under CPMG and even under SKMG are smaller yet than those under PMG, providing some support for the CPMG and SKMG procedures we are proposing in this paper to be effective pooling procedures for the number of observations available in many cross-country macroeconomic panels, even though the CPMG and SKMG procedures involve much weaker assumptions on which pooling is based than traditional pooling procedures such as dynamic fixed effects. Note that at least from a statistical perspective unconditional PPP, that is $\theta_1 = 1$ and $\theta_2 = -1$ across all values of the NFA to GDP ratio, is clearly rejected under the PMG, CPMG and SKMG procedures. All point estimates of the long-run parameters for θ_1 fall in the interval $[0.58, 0.83]$, and those for θ_2 fall into the interval $[-0.70, -0.54]$ and suggest a stronger long-run reaction of effective nominal exchange rates to domestic prices as compared to weighted foreign prices. It is quite remarkable that the estimates of the speed of adjustment coefficients all suggest rather fast adjustment to the long-run relation, in particular implying half lives between one and two years, much faster than what has typically been found in the literature and removing most of the stickiness puzzle that the previous literature on PPP (see, for example, Rogoff, 1996) has argued to be present.

While the average parameter estimates for CPMG and SKMG across all values of the NFA to GDP ratio are qualitatively similar to those obtained under the PMG approach, the idea underlying our CPMG and SKMG approaches is, of course, to report on the variation of the speed of adjustment and long-run coefficients across different values of the NFA to GDP ratio. Figures 2 to 16 pick up on this point. Figure 2 conveys that for our full sample of 65 countries there appears to be a strong dependence of the two long-run coefficients for domestic and weighted foreign prices on a country's international investment position as reflected by the smoothed NFA to GDP ratio (with the trend component of this ratio extracted using a ten-year filtering window). In particular, we find rather strong evidence that foreign exchange market participants appear to view the PPP relation as a strong anchor for the pricing of currencies in environments of limited negative NFA to GDP ratios. Under a limited negative NFA to GDP ratio, the long-run coefficients on domestic and weighted foreign prices are economically and partially even statistically insignificantly different from one and minus one, respectively.

The boundaries of this limited negative NFA to GDP ratio do differ, though, across the CPMG and SKMG procedures: about minus one to minus one and a half under the CPMG approach, and about minus one third to minus one under the SKMG approach. What is causing these differences? The curvatures of the Chebyshev polynomials entering the CPMG model are quite sensitive to the shape of the distribution of smoothed NFA to GDP ratios. This sensitivity is well conveyed in Figure 3, which shows that the curvatures of the Chebyshev polynomials increase substantially with lengthening of the window of observations used to calculate the trend component of the NFA to GDP ratio. This in turn is due to the fact that the mass of the distribution of this trend component shifts somewhat towards a range of NFA to GDP ratios involving more pronounced (negative) imbalances as the window length (ω) is increased. As the SKMG estimation results in Figure 4 display rather little such sensitivity, we prefer these, suggesting that for limited negative NFA to GDP ratios of about minus one third to minus one foreign exchange market participants appear to price medium- to long-run exchange rates in line with PPP. For yet larger imbalances of the international investment position or balanced international investment positions, the long-run equilibrium bears limited, little or even no resemblance with what PPP would suggest. When the NFA to GDP ratio is balanced, the SKMG approach suggests long-run elasticities of the effective nominal exchange rate with respect to domestic and weighted foreign prices of less than one half in absolute value.

Figure 2 also suggests that when there is a limited positive NFA to GDP ratio of around plus one third, then again medium- to long-run exchange rate pricing appears to be in line with PPP. However, the latter result needs to be expressed with more caution than the corresponding one for limited negative NFA to GDP ratios, as the number of limited positive NFA to GDP ratios in our sample is rather limited, and the long-run coefficient standard error bands specifically under SKMG widen sizeably for NFA to GDP ratios larger than plus one fifth.

Figures 5 and 6 report on the speed of adjustment coefficients for our full sample of 65 countries under the CPMG and SKMG approaches. Both under the CPMG and SKMG approaches the speed of adjustment coefficients in the range of limited negative NFA to GDP positions vary very little with the latter. Once more, however, it appears prudent not to put strong emphasis on results obtained for values of the smoothed NFA to GDP ratio larger than plus one fifth, given the limited number of observations in our sample involving such NFA to GDP ratios.

Overall, Figures 2 to 6 provide rather strong evidence that the NFA to GDP ratio significantly influences medium- to long-run exchange rate dynamics, but has limited, if any, effect on short-run dynamics. Medium- to long-run exchange rate dynamics particularly under limited negative NFA to GDP ratios seem well characterized by PPP. Figures 7 and 8 provide a robustness check on our results if the database of Lane and Milesi-Ferretti (2007) is used to compute the conditioning variable series $\{\tilde{z}_{i,t-1}\}$.[16] While the quantitative aspects of our results are affected by use of the Lane and Milesi-Ferretti (2007) database, our key qualitative finding that medium- to long-run exchange rate dynamics are significantly affected by changes in the smoothed NFA to GDP ratio, whereas short-run dynamics are not, is very much present still with the Lane and Milesi-Ferretti (2007) database also. Furthermore, under use of the Lane and Milesi-Ferretti (2007) database, too, there is still considerable evidence that there is an environment of limited negative NFA to GDP ratios under which medium- to long-run exchange rate pricing is well described by PPP.

5.2.3 Robustness Analysis Using Sample Splits

In addition to the international investment position of a country, it is likely that its medium- to long-run exchange rate dynamics are also influenced by other features of its macroeconomic and financial environment such as its income level, its exchange rate regime, its degree of price stability or its exposure to terms of trade shocks. One reason that the income level may matter is that if a country's NFA to GDP ratio was on average negatively related to its income level (and we will document evidence for this to be the case), then it would seem reasonable to conjecture that the range of NFA to GDP ratios for which foreign exchange market participants tend to price medium- to long-run exchange rates on the basis of PPP considerations is broader for low income countries than for middle or high income countries. Depending on the exchange rate regime, imbalances of real exchange rates may be judged to be more or less sustainable, resulting in differing degrees of conformity of the exchange rate with price fundamentals. Regarding price stability, a relatively low degree of price stability will *ceteris paribus* lead to a larger number of situations where imbalances will be sufficiently pronounced to require correction and thus might result in PPP equilibrium being a more relevant description of medium- to long-run exchange rate dynamics. The occurrence of relatively large terms of trade shocks affecting the international competitiveness of a country might lead to changes both in its international investment position and its effective exchange rate, implying a spurious relation between the NFA to GDP ratio and exchange rate dynamics.

As a first analysis to what extent our results regarding the role of a country's international

[16] As pointed out in Section 4, when using the Lane and Milesi-Ferretti (2007) database, the full sample can be expanded from 65 to 72 countries. For the reasons also discussed in Section 4 we nevertheless prefer to work with our own database.

investment position for medium- to long-run exchange rate dynamics are sensitive to also accounting for other factors of the macroeconomic and financial environment, we therefore include income level, exchange rate regime, price stability and terms of trade information in our analysis to disentangle the impact of these factors from that of the international investment position. It would clearly be appealing to allow for multi-variable conditioning through a CPMG or SKMG model that conditioned on a vector (rather than just a scalar) of state variables. However, in the set-up of our panel model of Section 3 this could easily result in a loss of parameter parsimony. How to best preserve parsimony in multi-variable CPMG and SKMG models is left for future research. In this paper, we instead confine ourselves to documenting the variation of the long-run elasticity of the effective nominal exchange rate with respect to domestic and weighted foreign prices across differing NFA to GDP ratios for four sample splits: (i) high and middle income countries vs. low income countries, (ii) floating exchange rate regimes vs. sticky exchange rate regimes, (iii) countries with a relatively low degree of price stability vs. countries with a relatively high degree of price stability and (iv) countries with on average large terms of trade shocks vs. countries with on average small terms of trade shocks.

Beginning with the split based on income levels, we split our sample of 65 countries into two groups, following the World Bank's income-based classification of countries. In particular, we collect countries categorized by the World Bank as "high income OECD countries", "high income non-OECD countries" and "upper middle income countries", labelling these as "high and middle income countries", while our group of "low income countries" comprises the World Bank's "lower middle income countries" and "low income countries". We find that for this sample split the average NFA to GDP ratio is equal to -0.187 for high and middle income countries, and is equal to -0.561 for low income countries. Figure 10 suggests that the relation between medium- to long-run exchange rate pricing and a country's international investment position that we found for the full sample of countries is also present both for our high and middle income countries sample as well as our low income countries sample, leading to similar types of curvature as for the full sample of countries. There are some quantitative qualifications, though. For the high and middle income countries sample the range of limited negative international investment positions for which we observe the strongest PPP-type medium- to long-run exchange rate pricing is associated with slightly smaller investment position imbalances than for the sample comprising all countries, appearing now at values for the NFA to GDP ratio around minus one third to minus one half. For the low income countries, the range of values for which the elasticities of the effective exchange rate with respect to prices approaches or even exceeds unity is broader, with PPP-type medium- to long-run exchange rate pricing materializing for NFA to GDP ratios from around minus one third to minus one and a quarter. Overall, it appears that – as we had conjectured – foreign exchange market participants for low income countries view PPP as a relevant anchor for a broader range of (negative) imbalances of the international investment position than for high and middle income countries.

To consider the role of exchange rate regimes for our results, we employ a data set on the *de facto* classification of exchange rate flexibility assembled by Levy-Yeyati and Sturzenegger (2005). Their data set contains an annual five-way categorization of the exchange rate regimes of *inter alia* all the 65 countries considered in our analysis as “flexible”, “dirty float”, “inconclusive”, “crawling peg” and “fixed”. We recode these five categories from a value of one for a “flexible” exchange rate regime to a value of five for a “fixed” exchange rate regime.[17]

Our sample split then constructs two groups of countries: The first group consists of countries for which the exchange rate classification code over our sample period is on average at most equal to three, and the second group features all countries with an exchange rate classification code being on average larger than three over our sample period.[18] Figure 12 reports on our exchange rate regime based sample split. Inspection of this figure reveals that the curvatures of the functions depicting the long-run coefficients in dependence on the NFA to GDP ratio are somewhat more pronounced for fixed exchange rate regimes than for floating ones. However, for both fixed and floating regimes we find strong adherence to medium- to long-run exchange rates being priced on the basis of a PPP-type relation under limited negative NFA to GDP ratios. This suggests that our international investment position conditioning is separate from an influence of exchange rate regimes on medium- to long-run exchange rate dynamics.

To consider the impact of a country’s degree of price stability on our results, we split our sample into one group of countries for which the average rate of inflation over our sample period exceeded twelve percent (we label countries in this group as those exhibiting a “low degree of price stability”) as well as a second group of countries for which the average rate of inflation over our sample period was twelve percent or lower (we label countries in this group as those exhibiting a “high degree of price stability”). Figure 14 reports on this sample split. The figure suggests that the magnitudes of international investment position imbalances under which foreign exchange markets in the medium to long run price currencies in line with PPP are somewhat sensitive to the degree of price stability. Limited negative NFA to GDP ratios leading to PPP-type pricing of exchange rates for countries with a low degree of price stability are centered around minus three quarters to minus one, but for countries with a

[17]The Levy-Yeyati and Sturzenegger (2005) data set spans the period 1974 to 2004; we assume that all exchange rates were “fixed” over the period 1970 to 1973.

[18]It should be kept in mind, of course, that we work with effective exchange rates spanning a broad range of countries, whereas the Levy-Yeyati and Sturzenegger (2005) classification concerns fluctuations of one currency relative to one other, selected currency (often the U.S. Dollar, the Pound Sterling, the Deutsche Mark or the French Franc) only.

high degree of price stability are in absolute value a bit smaller, namely are centered around minus one half. In other words, under a relatively high degree of price stability, foreign exchange markets return to PPP fundamentals under lower degrees of external imbalance than in environments of relatively low degrees of price stability. The qualitative pattern of adjustment towards PPP-type pricing when a country's international investment position moves into imbalance is surprisingly similar for countries with low and with high degrees of price stability.

Finally, we evaluate the implications of differences in the countries' exposure to terms of trade shocks. We split our sample into two groups exhibiting on average relatively large and relatively small terms of trade shocks, respectively. Given that data on a country's terms of trade are only available in index form, such that the level itself is not interpretable, we extract shocks by fitting simple autoregressive integrated moving average (ARIMA) models to annual terms of trade time series obtained from the World Bank's World Development Indicators. The lag orders for these models are determined via the Akaike Information Criterion allowing for a maximum lag order of three for both the autoregressive and the moving average parts. The degree of integration is determined according to an Augmented Dickey-Fuller test at the 5% significance level. The model includes a time trend and a constant for the level specification and a constant for the specification using first differences of the time series. Based on the variance of the shocks that we obtain from the estimated time series model, we split our sample into a group of countries that exhibit a shock variance that is larger than or equal to the average shock variance across all countries, labelling these "countries with large terms of trade shocks", and a group of countries that exhibit a shock variance that is smaller than the average shock variance across all countries, labelling these "countries with small terms of trade shocks". Figure 16 suggests that PPP for countries with small terms of trade shocks continues to hold in environments of limited negative NFA to GDP positions. For countries with large terms of trade shocks the evidence is not as clear; the long-run coefficient on domestic prices shows the same type of curvature as in the full sample, whereas the long-run coefficient on foreign prices shows relatively weak variation as a function of the NFA to GDP position in the range of NFA to GDP ratios for which a satisfactory number of data points is available. This result may, however, be driven by the limited range of NFA to GDP ratios we have available for countries with large terms of trade shocks. Overall, we view the the results in Figure 16 as soundly refuting the hypothesis that our results concerning the conditional validity of PPP would be driven by countries with large terms of trade shocks.

6 Conclusion

In this paper we have revisited medium- to long-run exchange rate determination, focusing on the role of international investment positions. To do so, we have developed a new econometric framework accounting for conditional long-run homogeneity in heterogeneous dynamic panel data models. In particular, in our model the long-run relationship between effective exchange rates and domestic as well as weighted foreign prices has been specified as a function of a country's international investment position as measured by a smoothed predetermined value of the NFA to GDP ratio. We have found rather strong support for PPP in environments of limited negative NFA to GDP ratios, but not in environments of balanced NFA to GDP positions, or negative NFA to GDP ratios that are rather large in absolute value. We have also adduced evidence that the conditioning of PPP on a country's international investment position remains important when allowing for other features of the macroeconomic environment, such as the income level, the exchange rate regime, the degree of price stability and the magnitude of terms of trade shocks.

Our future research will in particular address two issues: (i) the extension of CPMG and SKMG models to a parsimonious multivariate conditioning framework, and (ii) the extension of at least part of our database to bilateral measurement of international capital flows, allowing to address issues of links between the sources and destinations of capital flows as well as their effects on stocks of international investment positions on the one hand and macroeconomic and financial market outcomes on the other hand.

Tables and Figures

Table 1: Stationarity Properties for 65 Countries, 1970 to 2004

(a) *Panel Unit Root Test*

	Level	First Difference
e	$\mathbf{-3.0585}$	$\mathbf{-3.9439}$
p	-2.0163	$\mathbf{-2.6866}$
p^*	-2.3704	$\mathbf{-2.8502}$

(b) *Panel Cointegration Test*

	$\omega = 3$	$\omega = 5$	$\omega = 7$	$\omega = 10$
$e - \theta_1(\tilde{z})p - \theta_2(\tilde{z})p^*$	$\mathbf{-4.8255}$	$\mathbf{-4.8354}$	$\mathbf{-4.8510}$	$\mathbf{-4.8603}$

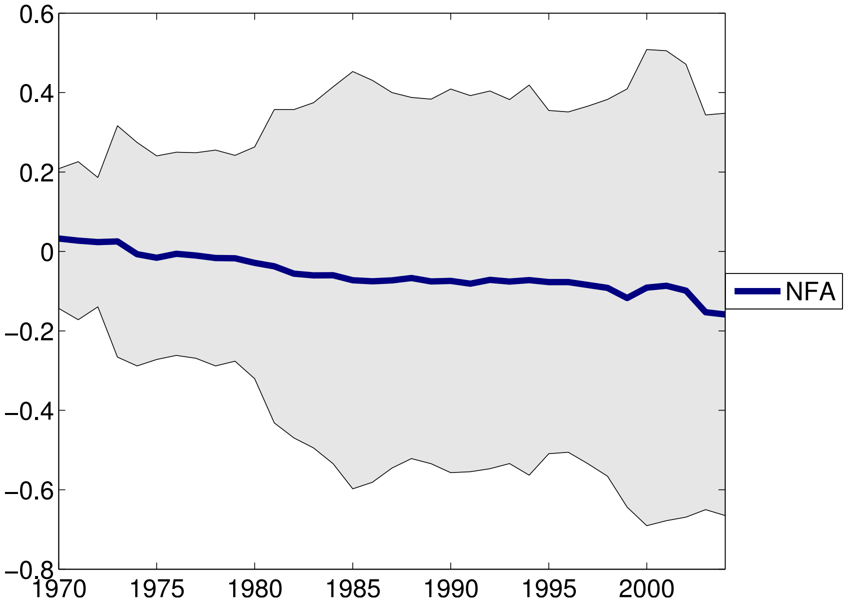
Notes: The panel unit-root test (Part (a)) is computed according to Pesaran (2007) and has a non-standard distribution under the null hypothesis of a unit root in the time series under consideration for all countries. Under the alternative hypothesis, the time series under consideration is I(0) for a non-vanishing share of countries. Levels of the variables are modelled with a constant and a linear time trend, whereas the specifications for first differences of the variables include a constant only. The critical value at the 5% (1%) significance level for the level of a series is -2.58 (-2.69) and -2.08 (-2.19) for the first difference of a series. The panel cointegration test statistics (Part (b)) are distributed standard Normal under the null of no cointegration (see Westerlund, 2005), with the alternative hypothesis being that cointegration prevails for all countries. The test statistics were computed using Chebyshev polynomials of order three for the estimation of conditionally homogeneous long-run coefficients and are reported for different window widths ω for the filtering of the conditioning variable, $\tilde{z}$. The lag orders in both parts of the table were selected according to the Akaike Information Criterion based on a maximum lag order of 2, but the results are robust to other choices, as well as to lag selection on the basis of other information criteria such as the Schwarz Bayesian Criterion. Figures in bold face denote significance at the 5% level.

Table 2: Speed of Adjustment and Long-Run Coefficients (Averages)

	MG	PMG	CPMG	SKMG
α	$\mathbf{-0.4945}$	$\mathbf{-0.3732}$	$\mathbf{-0.3979}$	$\mathbf{-0.3674}$
	(0.0366)	(0.0321)	(0.0314)	(0.0001)
θ_1	-0.1938	$\mathbf{0.8231}$	$\mathbf{0.8176}$	$\mathbf{0.5881}$
	(0.5433)	(0.0231)	(0.0128)	(0.0205)
θ_2	$\mathbf{-0.6549}$	$\mathbf{-0.5490}$	$\mathbf{-0.6916}$	$\mathbf{-0.5530}$
	(0.3051)	(0.0722)	(0.0128)	(0.0175)

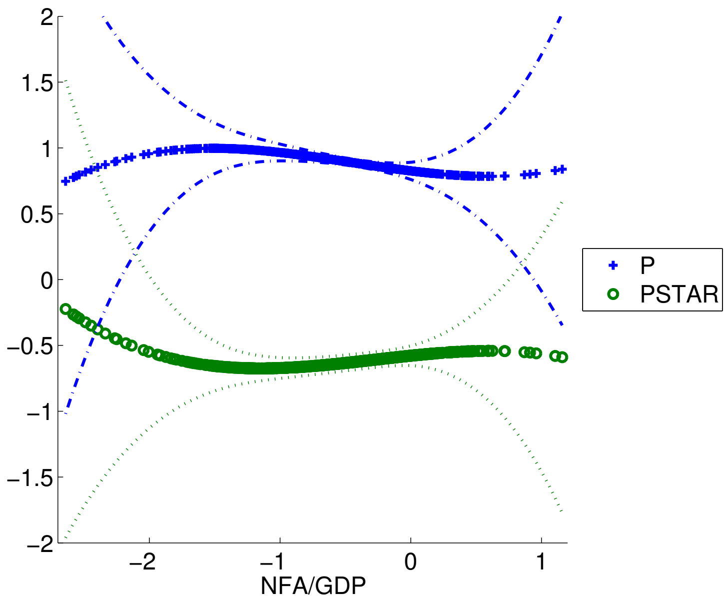
Notes: Cross-country averages of the speed of adjustment coefficient α and the long-run coefficients on the domestic (θ_1) and weighted foreign (θ_2) prices in Equation (26). PPP would suggest that $\alpha < 0$, $\theta_1 = 1$, and $\theta_2 = -1$. Under CPMG and SKMG, country-specific coefficients are evaluated at the mean of the conditioning variable $\tilde{z}_{i,t-1}$, with the series for $\{\tilde{z}_{i,t-1}\}$ constructed under $\omega = 10$. The lag length is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard errors are given in parentheses below the coefficients; figures in bold face denote significance at the 5% level.

Figure 1: Net Foreign Assets as a Ratio to GDP, 1970 to 2004

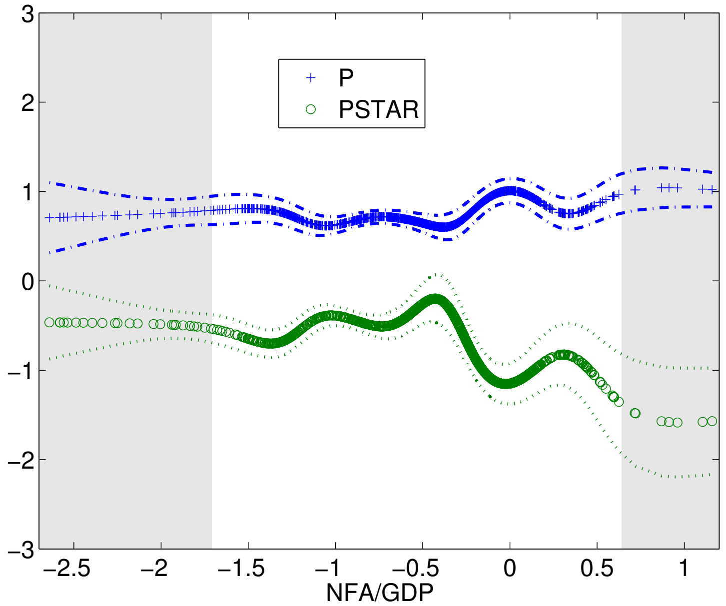


Notes: The solid line represents the aggregate of NFA divided by aggregate GDP across our sample of 65 countries, with the standard deviation across countries of the NFA to GDP ratio represented by the boundaries of the shaded area.

Figure 2: Long-Run Coefficients for 65 Countries, 1970 to 2004



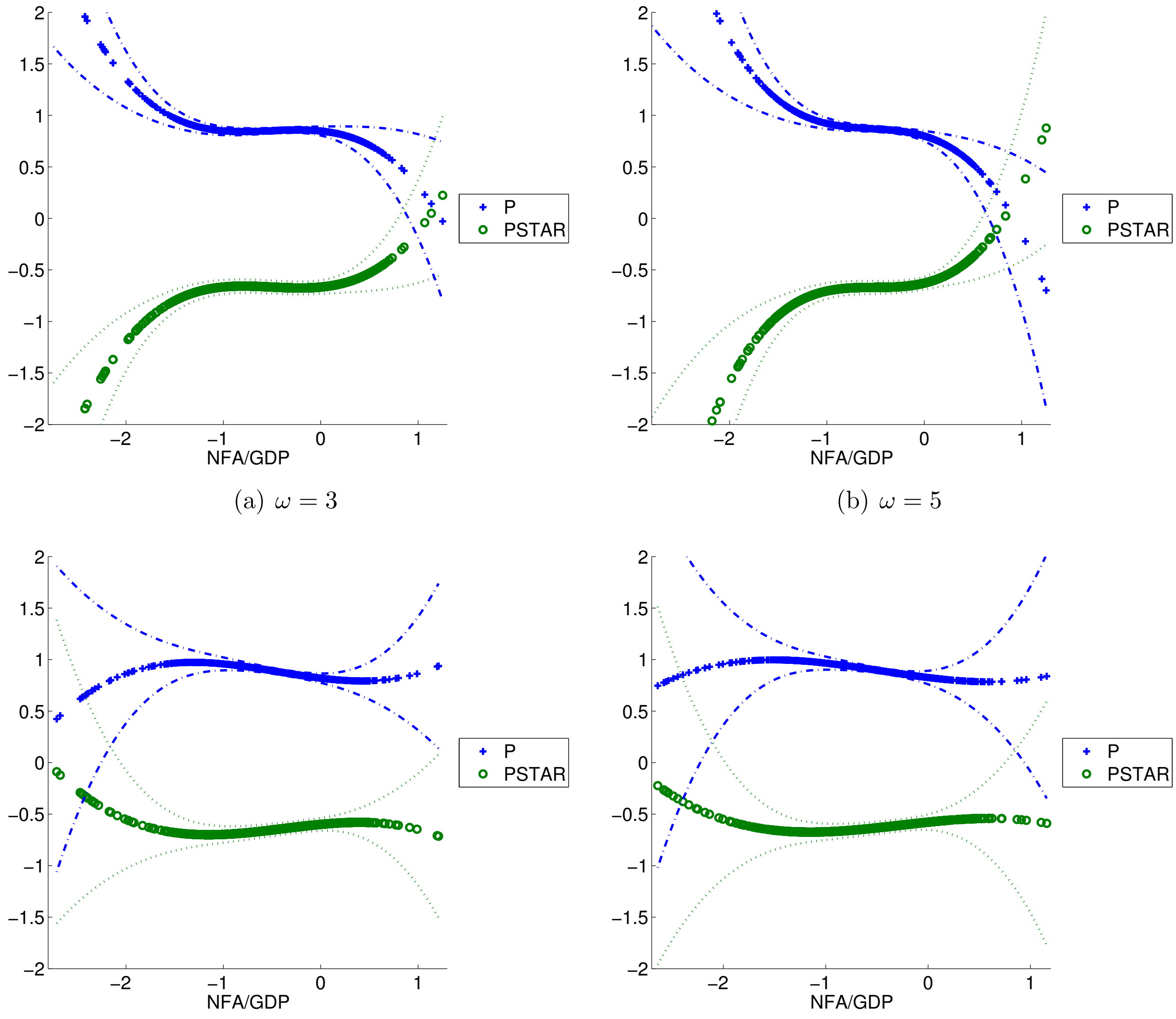
(a) CPMG Approach, $\omega = 10$



(b) SKMG Approach, $\omega = 10$

Notes: Estimates of the conditional long-run coefficients in the relation between the effective nominal exchange rate and domestic as well as weighted foreign prices in the panel ARDL model (26), with the conditioning variable being defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over a window of width $\omega = 10$. The CPMG approach uses Chebyshev polynomials of order three in the conditioning variable; the SKMG approach uses local kernels in the conditioning variable. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

Figure 3: Long-Run Coefficients for 65 Countries, 1970 to 2004:
CPMG Approach

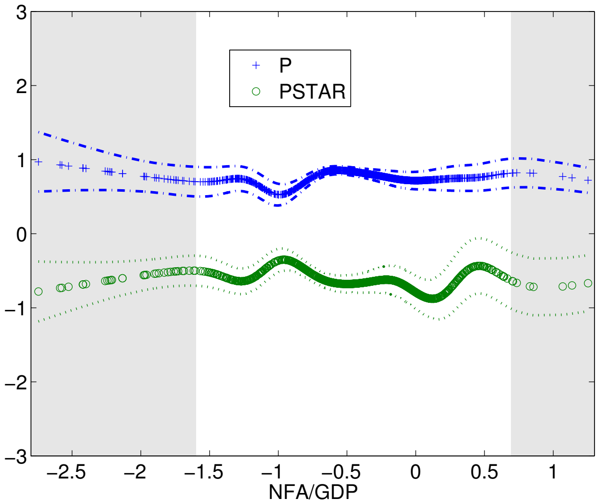


(a) $\omega = 3$ (b) $\omega = 5$

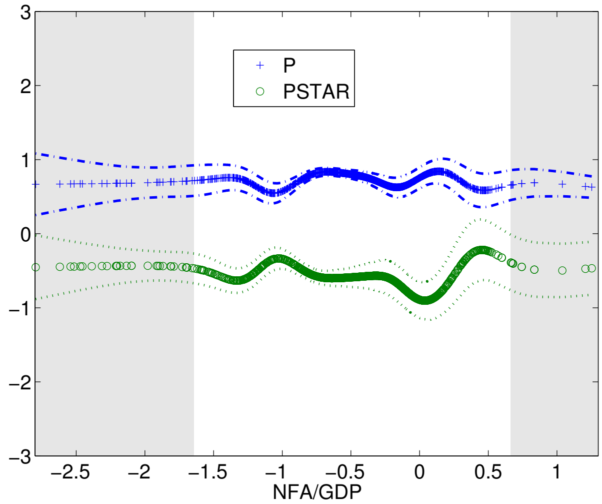
(c) $\omega = 7$ (d) $\omega = 10$

Notes: Estimates of the conditional long-run coefficients in the relation between the effective nominal exchange rate and domestic as well as weighted foreign prices in the panel ARDL model (26) using Chebyshev polynomials of order three in the conditioning variable, the latter being defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over different window widths ω. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

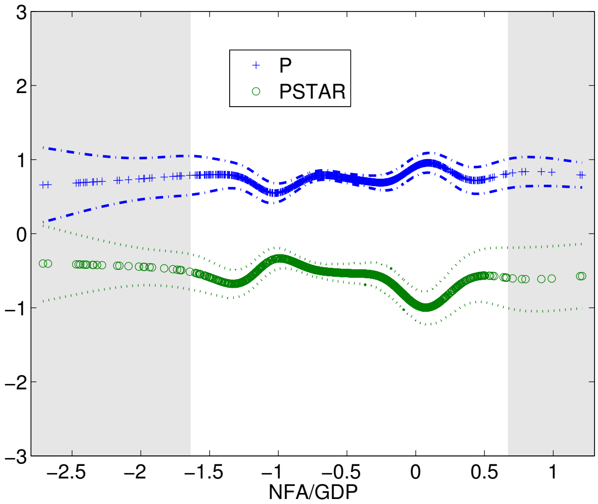
Figure 4: Long-Run Coefficients for 65 Countries, 1970 to 2004:
SKMG Approach



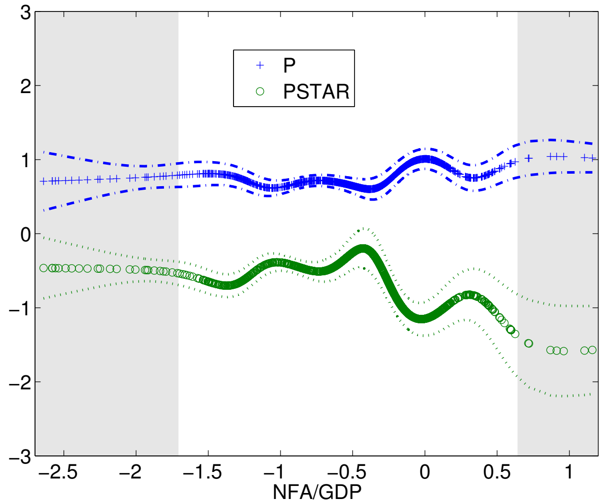
(a) $\omega = 3$



(b) $\omega = 5$



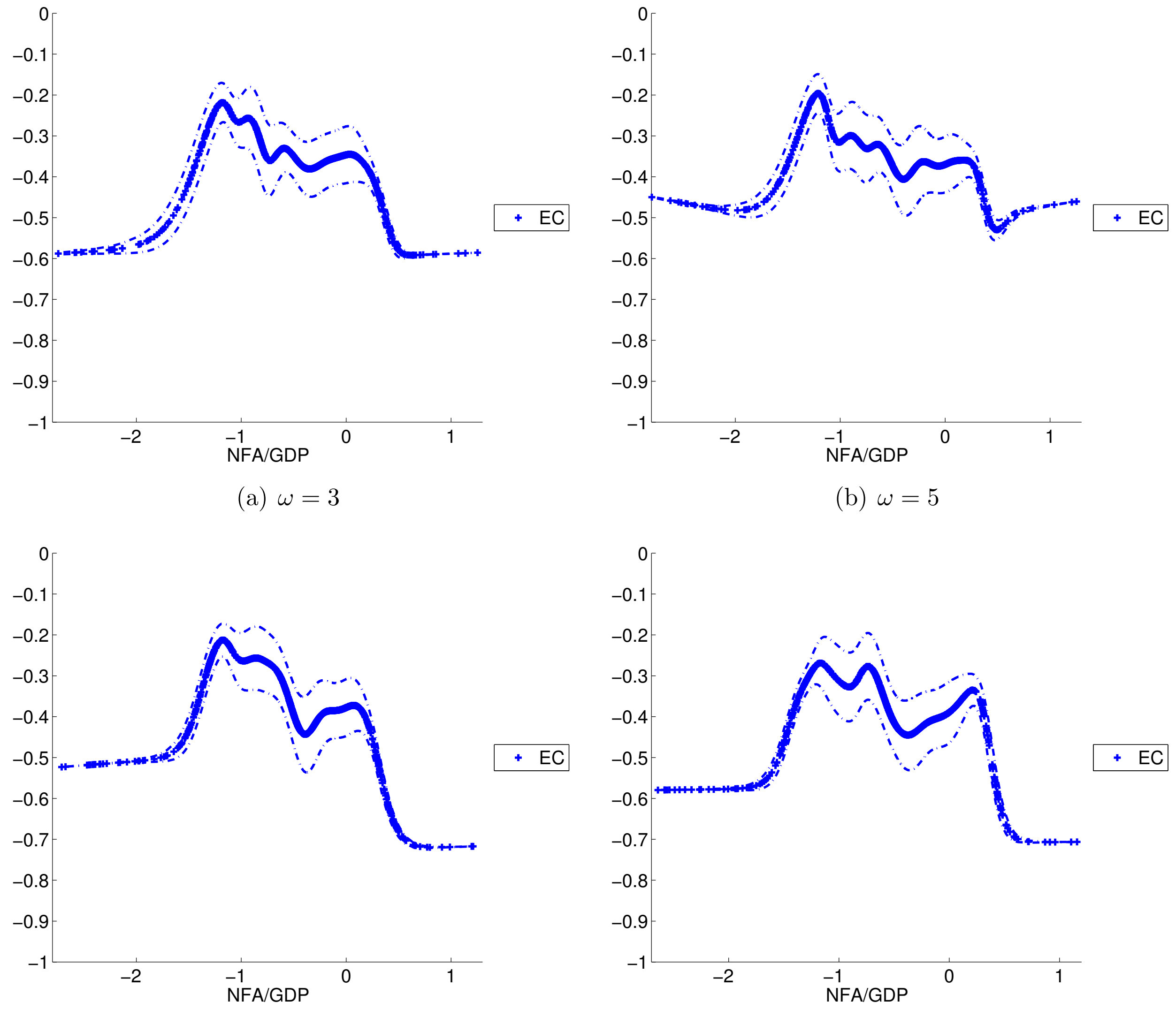
(c) $\omega = 7$



(d) $\omega = 10$

Notes: Estimates of the conditional long-run coefficients in the relation between the effective nominal exchange rate and domestic as well as weighted foreign prices in the panel ARDL model (26) using local kernels in the conditioning variable, the latter being defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over different window widths ω. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

Figure 5: Speed of Adjustment Coefficients for 65 Countries, 1970 to 2004: CPMG Approach



(a) $\omega = 3$

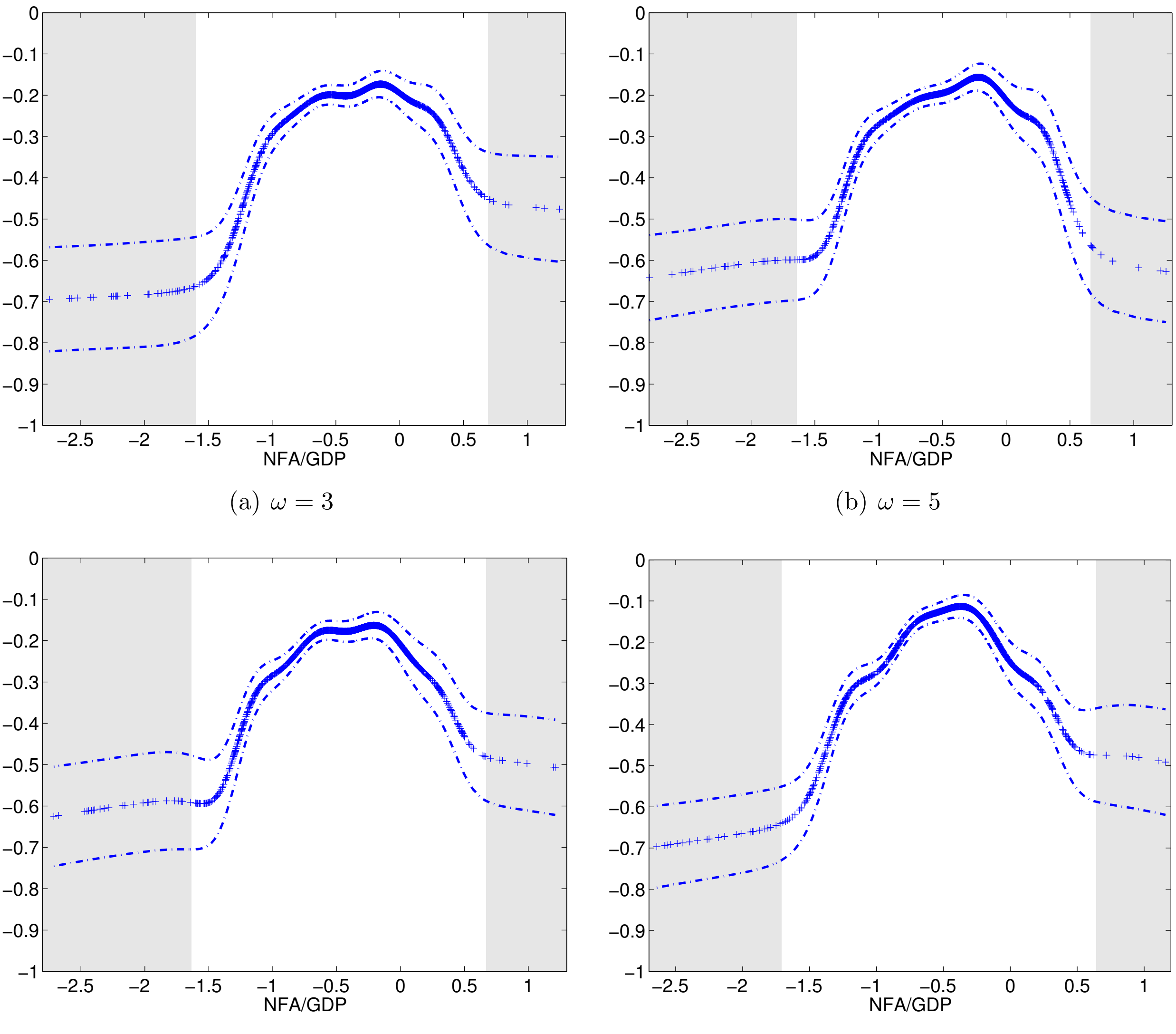
(b) $\omega = 5$

(c) $\omega = 7$

(d) $\omega = 10$

Notes: Smoothed mean group estimates of the speed of adjustment coefficients in the panel ARDL model (26) using Chebyshev polynomials of order one in the conditioning variable, the latter being defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over different window widths ω. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

Figure 6: Speed of Adjustment Coefficients for 65 Countries, 1970 to 2004: SKMG Approach



(a) $\omega = 3$

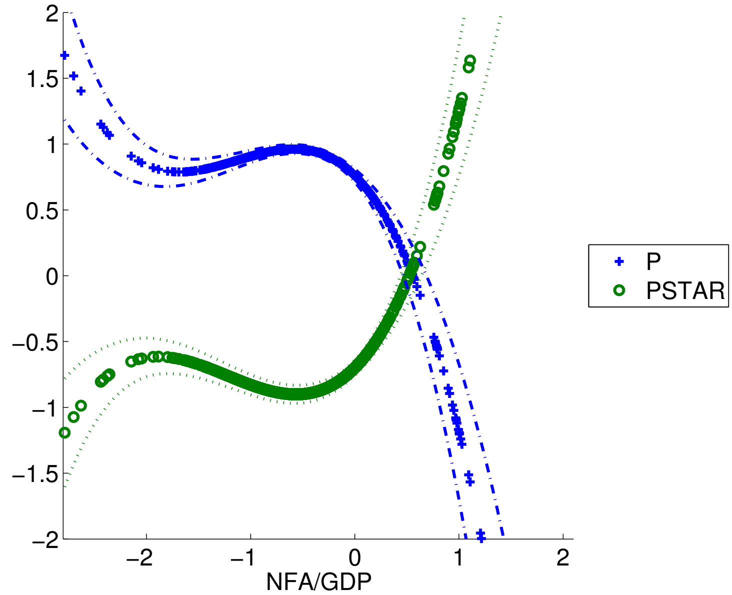
(b) $\omega = 5$

(c) $\omega = 7$

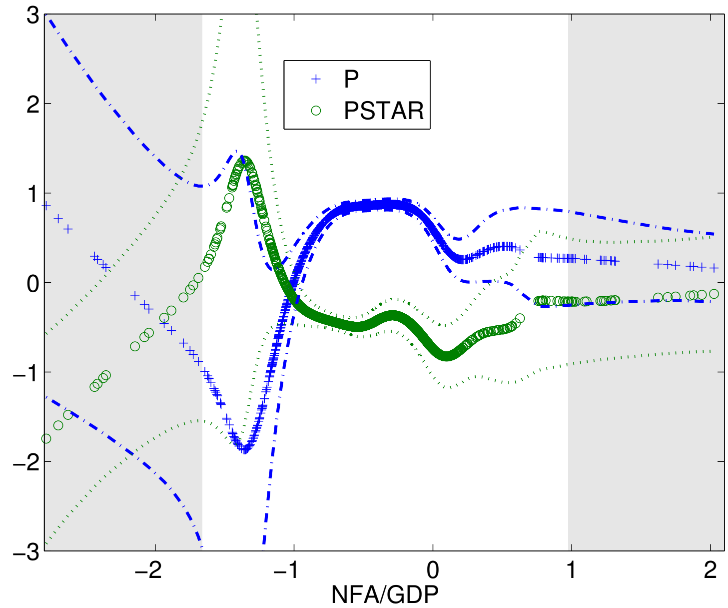
(d) $\omega = 10$

Notes: Estimates of the speed adjustment coefficients in the panel ARDL model (26) using local kernels in the conditioning variable, the latter being defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over different window widths ω. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

Figure 7: Long-Run Coefficients for 72 Countries using Lane and Milesi-Ferretti (2007) Data, 1970 to 2004



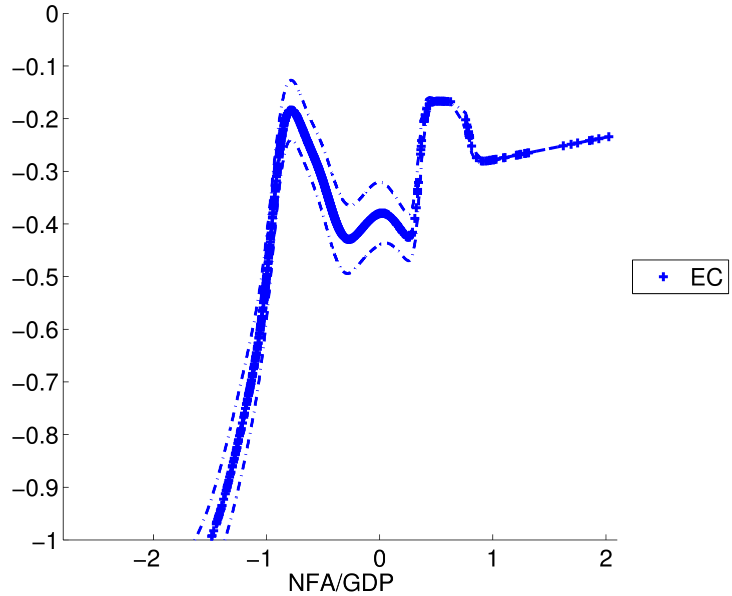
(a) CPMG Approach, $\omega = 10$



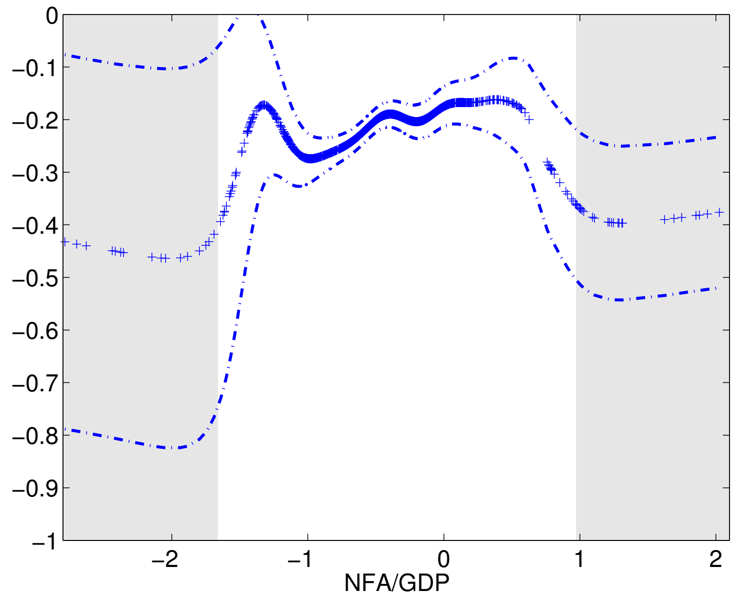
(b) SKMG Approach, $\omega = 10$

Notes: See Figure 2.

Figure 8: Speed of Adjustment Coefficients for 72 Countries using Lane and Milesi-Ferretti (2007) Data, 1970 to 2004



(a) CPMG Approach, $\omega = 10$

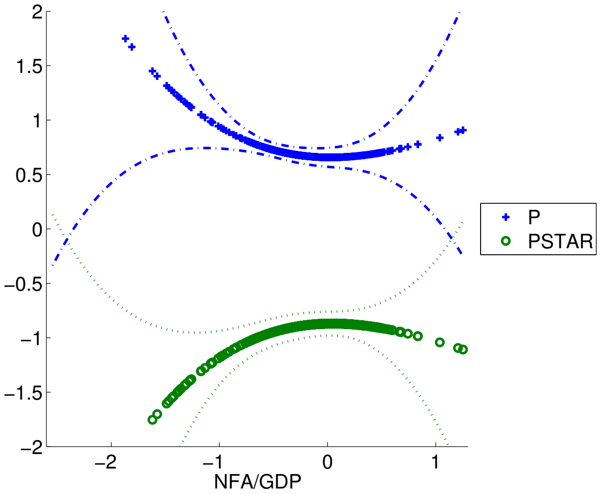


(b) SKMG Approach, $\omega = 10$

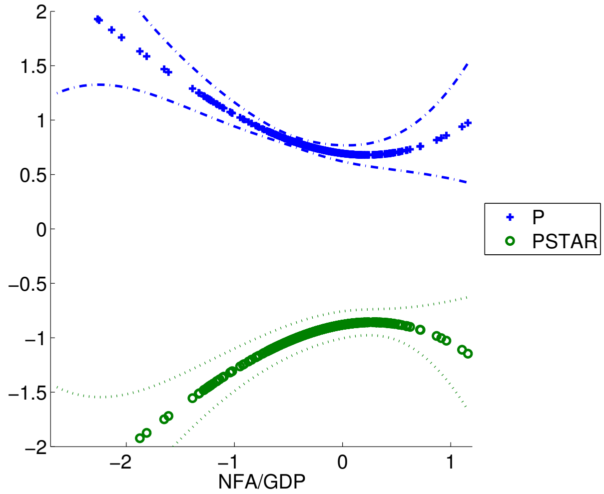
Notes: Part (a): Smoothed mean group estimates of the speed of adjustment coefficients in the panel ARDL model (26) using Chebyshev polynomials of order one in the conditioning variable; part (b): Estimates of the speed of adjustment coefficients in the panel ARDL model (26) using local kernels in the conditioning variable. For both parts, the conditioning variable is defined as the one-sided Hodrick-Prescott filtered NFA to GDP ratio over a window of width $\omega = 10$. The lag order is selected according to the Akaike Information Criterion with a maximum lag order of 2. Standard error bands denote the 95% confidence intervals of the coefficient estimates.

Figure 9: Income-Based Sample Split, 1970 to 2004

High and Middle Income Countries, CPMG Approach, 31 Countries

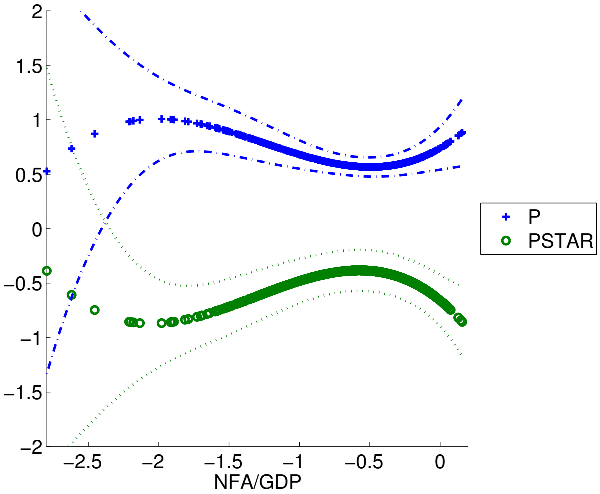


(a) $\omega = 5$

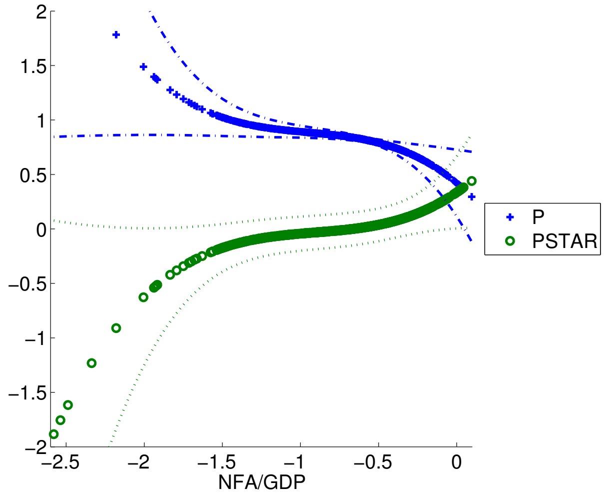


(b) $\omega = 10$

Low Income Countries, CPMG Approach, 34 Countries



(c) $\omega = 5$

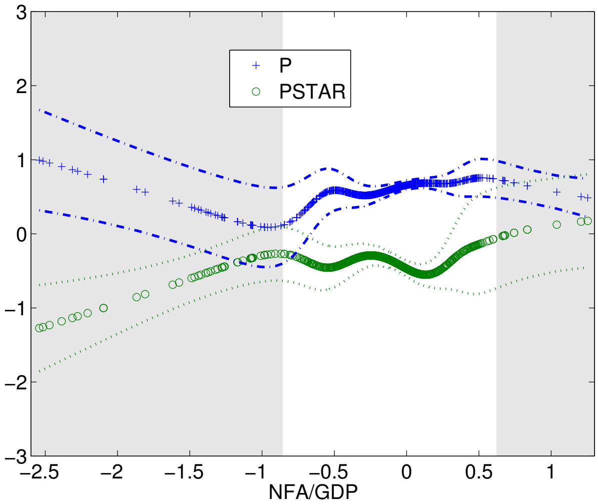


(d) $\omega = 10$

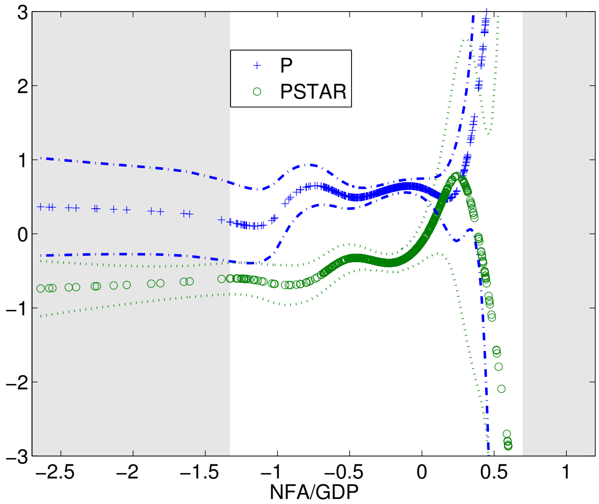
Notes: See Figure 3.

Figure 10: Income-Based Sample Split, 1970 to 2004

High and Middle Income Countries, SKMG Approach, 31 Countries

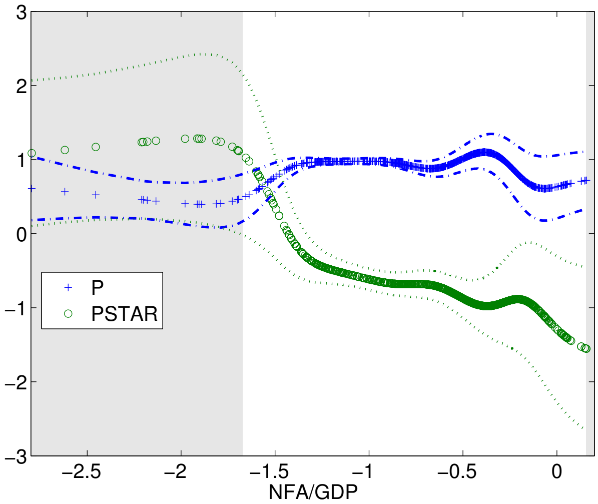


(a) $\omega = 5$

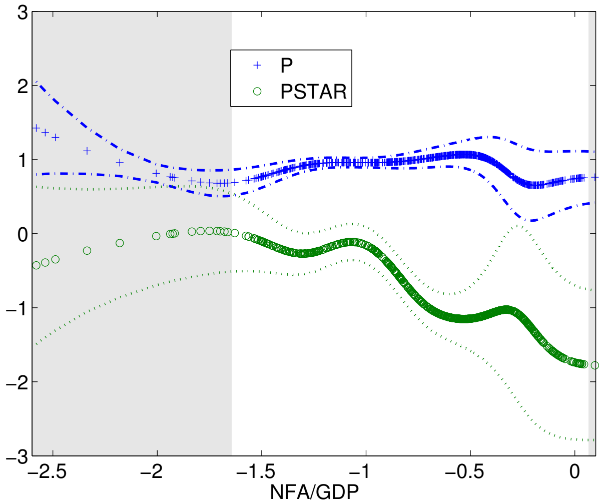


(b) $\omega = 10$

Low Income Countries, SKMG Approach, 34 Countries



(c) $\omega = 5$

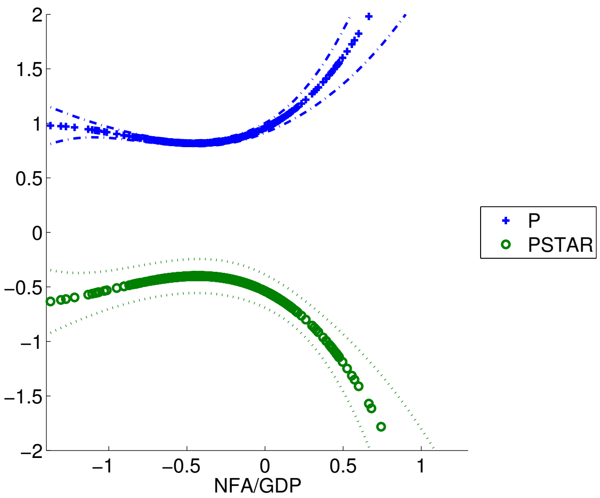


(d) $\omega = 10$

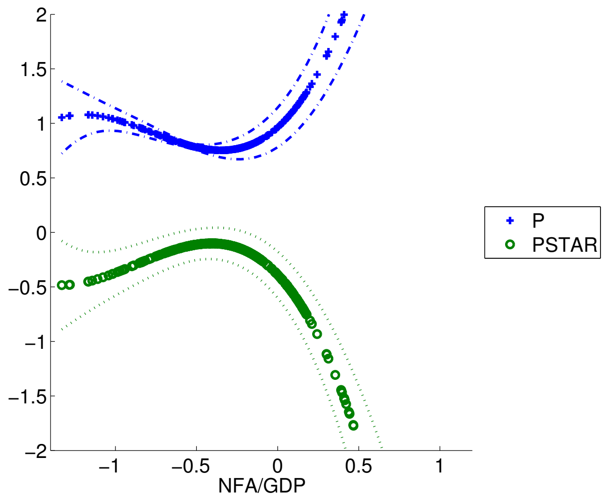
Notes: See Figure 4.

Figure 11: Exchange Rate Regime-Based Sample Split, 1970 to 2004

Floating Exchange Rate Regimes, CPMG Approach, 20 Countries

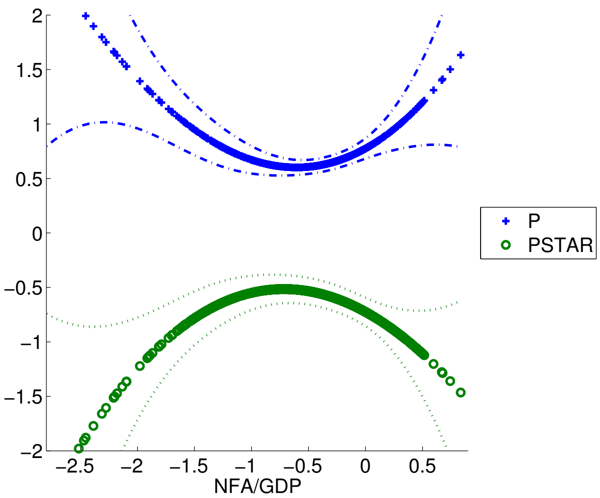


(a) $\omega = 5$

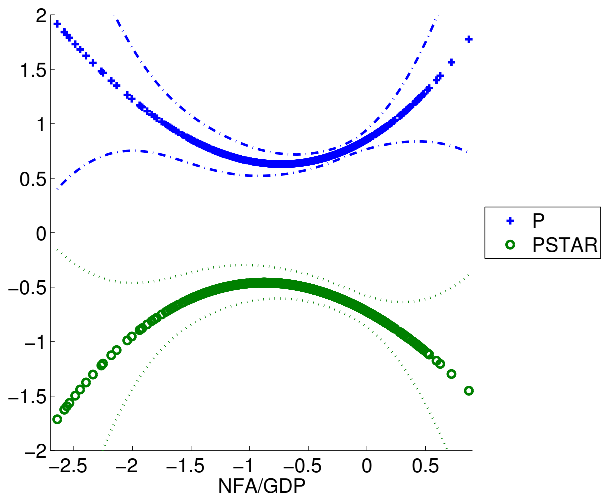


(b) $\omega = 10$

Fixed Exchange Rate Regimes, CPMG Approach, 45 Countries



(c) $\omega = 5$

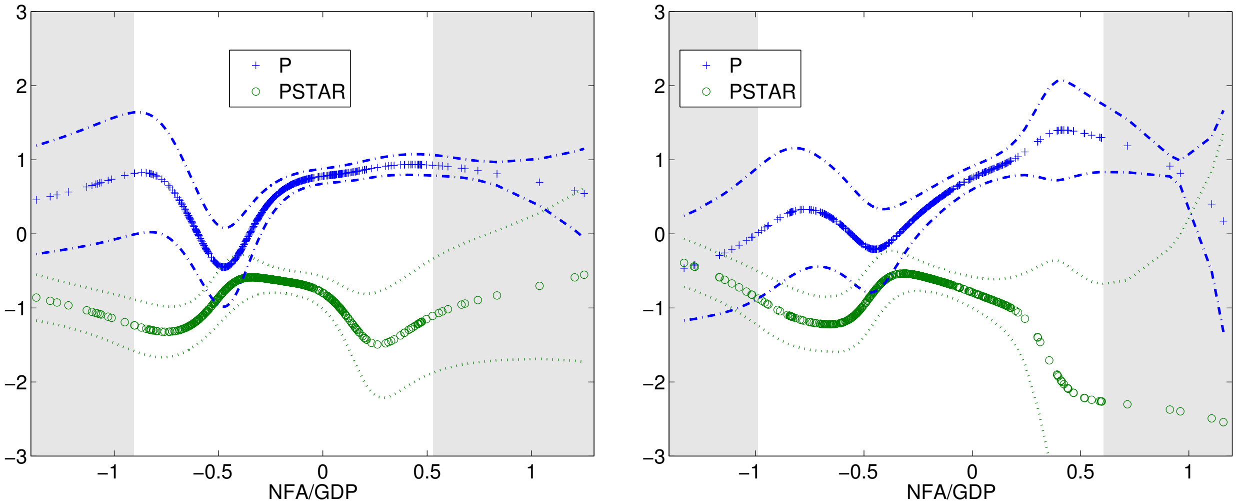


(d) $\omega = 10$

Notes: See Figure 3.

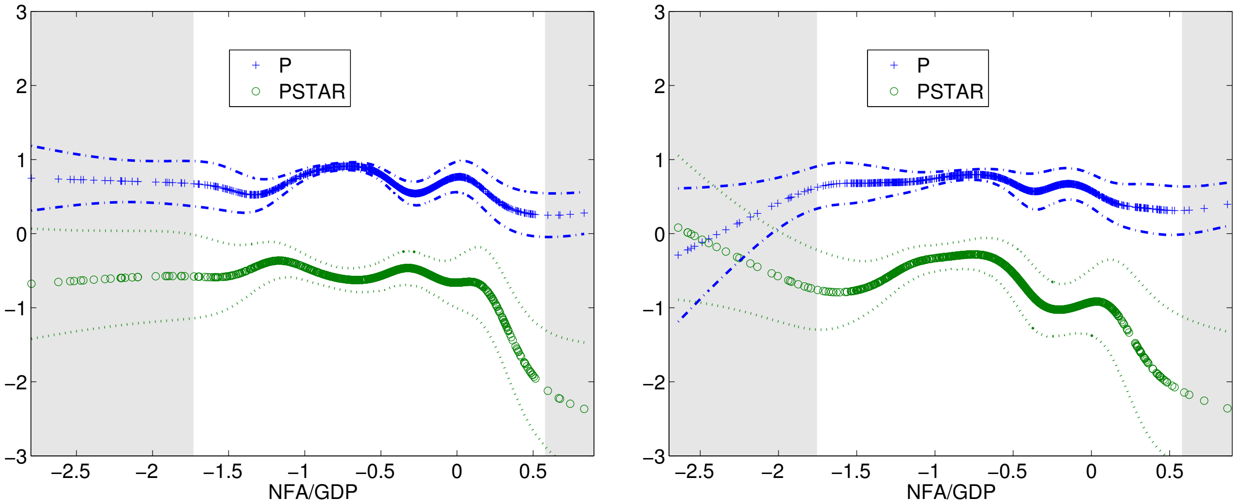
Figure 12: Exchange Rate Regime-Based Sample Split, 1970 to 2004

Floating Exchange Rate Regimes, SKMG Approach, 20 Countries



(a) $\omega = 5$ (b) $\omega = 10$

Fixed Exchange Rate Regimes, SKMG Approach, 45 Countries

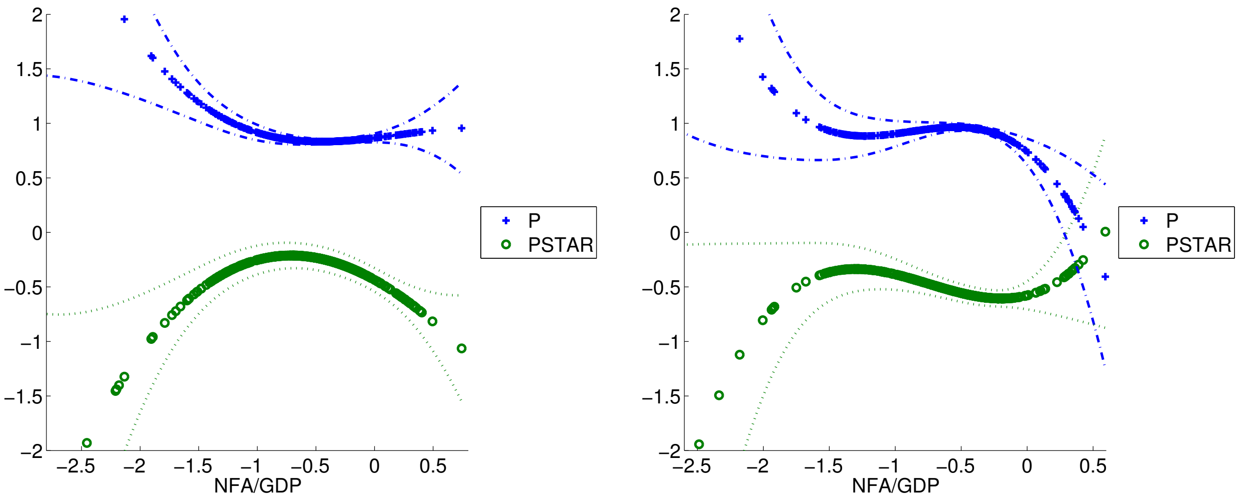


(c) $\omega = 5$ (d) $\omega = 10$

Notes: See Figure 4.

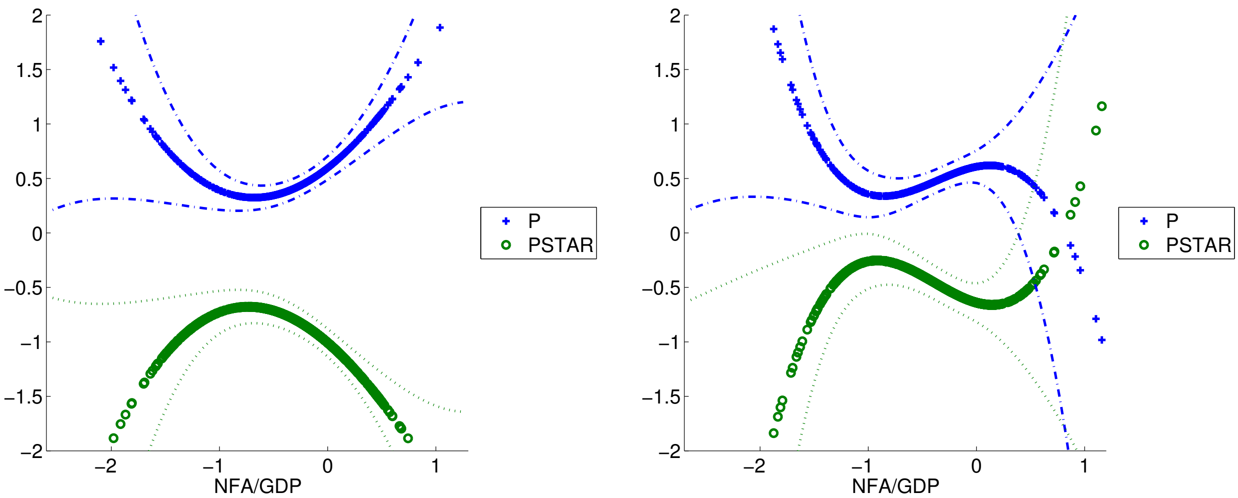
Figure 13: Price Stability-Based Sample Split, 1970 to 2004

Countries with Low Degree of Price Stability, CPMG Approach, 24 Countries



(a) $\omega = 5$ (b) $\omega = 10$

Countries with High Degree of Price Stability, CPMG Approach, 41 Countries

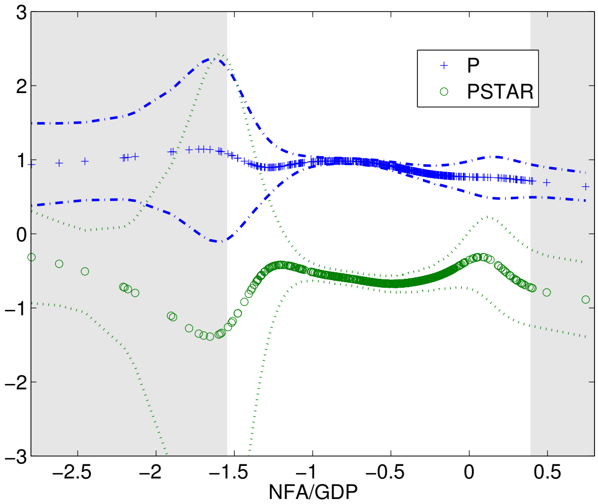


(c) $\omega = 5$ (d) $\omega = 10$

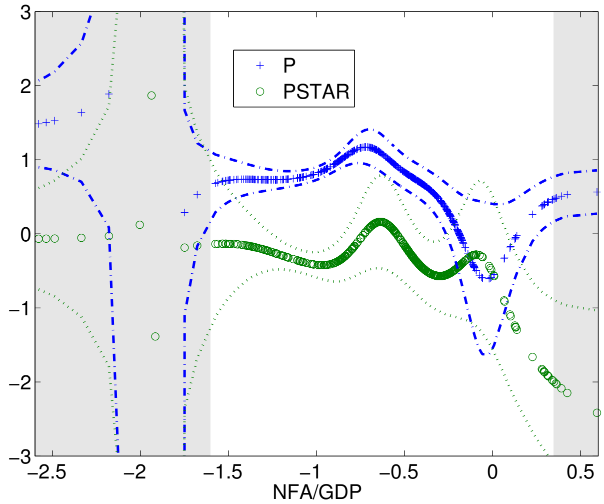
Notes: See Figure 3.

Figure 14: Price Stability-Based Sample Split, 1970 to 2004

Countries with Low Degree of Price Stability, SKMG Approach, 24 Countries

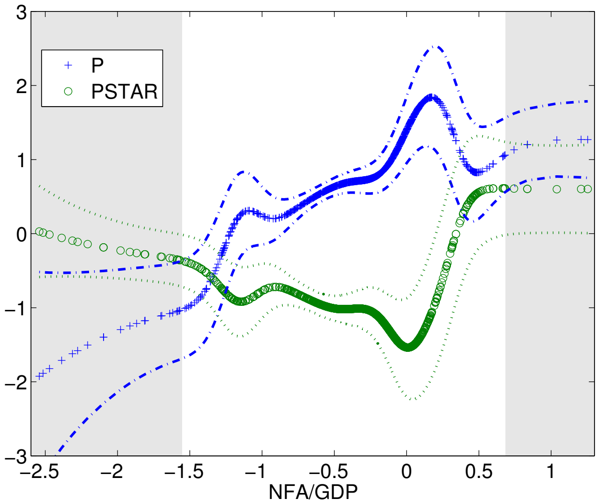


(a) $\omega = 5$

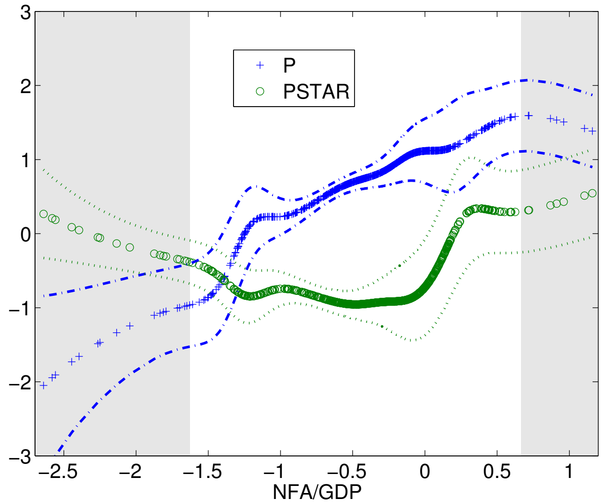


(b) $\omega = 10$

Countries with High Degree of Price Stability, SKMG Approach, 41 Countries



(c) $\omega = 5$

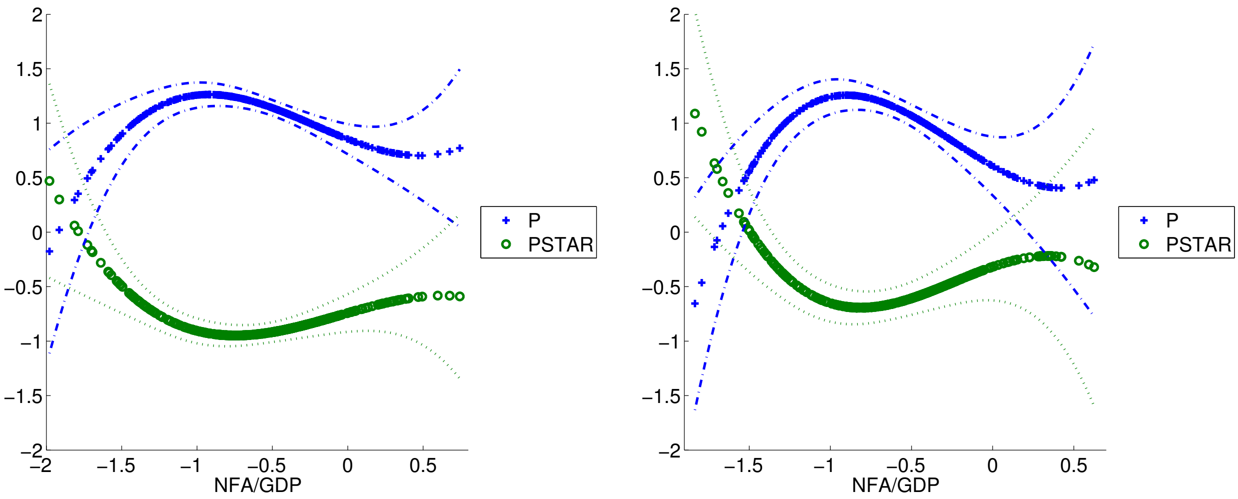


(d) $\omega = 10$

Notes: See Figure 4.

Figure 15: Terms of Trade Shock-Based Sample Split, 1970 to 2004

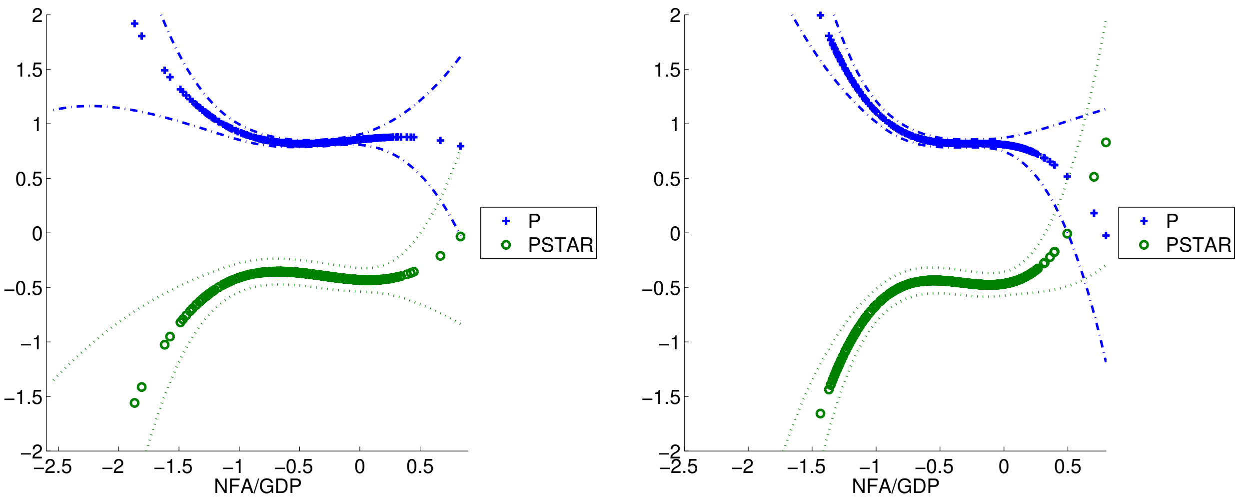
Countries with Large Terms of Trade Shocks, CPMG Approach, 18 Countries



(a) $\omega = 5$

(b) $\omega = 10$

Countries with Small Terms of Trade Shocks, CPMG Approach, 36 Countries



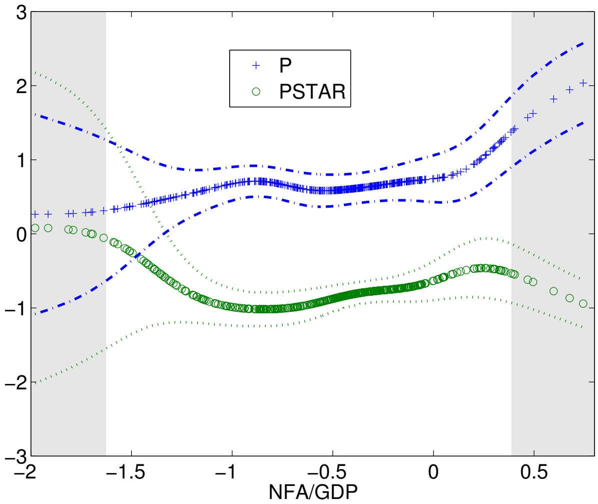
(c) $\omega = 5$

(d) $\omega = 10$

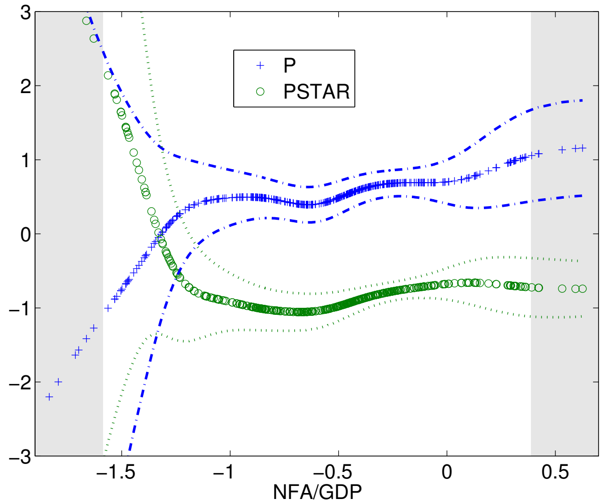
Notes: See Figure 3.

Figure 16: Terms of Trade Shock-Based Sample Split, 1970 to 2004

Countries with Large Terms of Trade Shocks, SKMG Approach, 18 Countries

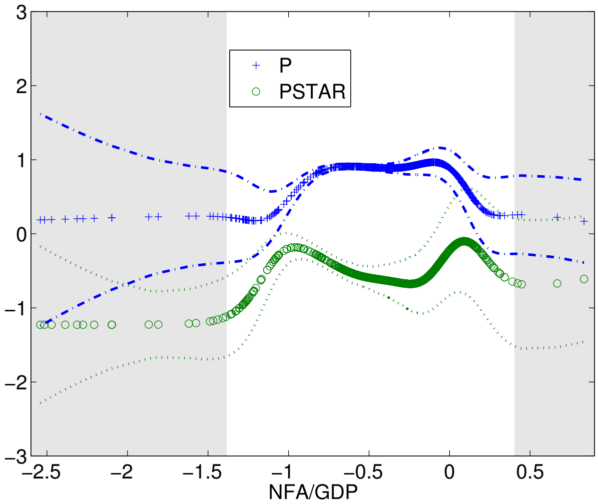


(a) $\omega = 5$

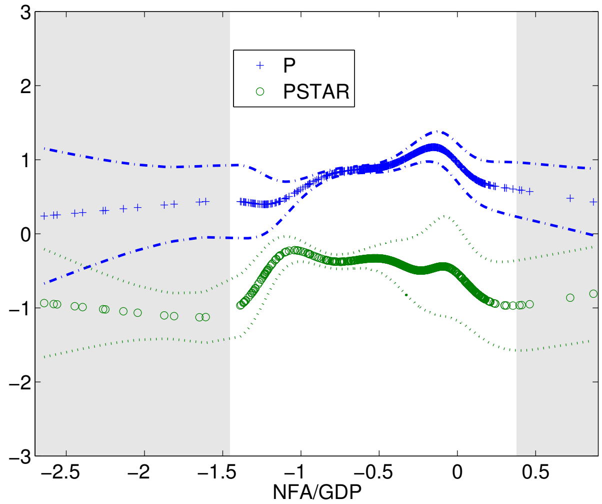


(b) $\omega = 10$

Countries with Small Terms of Trade Shocks, SKMG Approach, 36 Countries



(c) $\omega = 5$



(d) $\omega = 10$

Notes: See Figure 4.

Appendices

A Computation of Smoothed Mean Group Estimates and Standard Errors for Speed of Adjustment Coefficients

Under the CPMG approach, we estimate N separate functional forms for the speed of adjustment coefficients, such that

$$\hat{\alpha}_{it}^{(j)} = \hat{\alpha}_j(z_{i,t-1}), \quad i = 1, 2, ..., N, \ t = 1, 2, ..., T, \ j = 1, 2, ..., N, \tag{A.1}$$

represents the estimate of the speed of adjustment evaluated at observation (i, t) using the functional form estimated for country j. Similar to the MG approach we now want to obtain an estimate of the mean relationship in the panel between the speed of adjustment coefficient and the conditioning state variable $z_{i,t-1}$ by averaging across country-specific estimates of this relationship. The country-specific functional forms are based on Chebyshev polynomials up to order τ, with polynomial terms $c_s(z_{i,t-1})$ and parameters $\gamma_{sj}^{(\alpha_j)}$, $s = 0, 1, ..., \tau$. The mean coefficient at the point $z_{i,t-1}$ should therefore be an average of the coefficients implied by each polynomial. However, the polynomial function for each country's speed of adjustment coefficient is estimated on the basis of the observations for that country only and therefore might only be valid in a limited range of values for $z_{i,t-1}$. Extrapolating this function to values that are far from this range might lead to large outliers which can distort the panel MG coefficient.

We therefore compute a weighted average of the heterogeneous coefficients $\hat{\alpha}_j(z_{i,t-1})$, where the weights decrease with the distance of $z_{i,t-1}$ from the mean for country j, $\bar{z}_j$. The distance may be incorporated using a kernel specification. In particular, let $\hat{\boldsymbol{\gamma}}_j^{(\alpha_j)}$ be the $\tau + 1$ vector of estimated polynomial coefficients for country j. Then

$$\hat{\alpha}_{it}^{(j)} = \hat{\boldsymbol{\gamma}}_j^{(\alpha_j)\prime} \boldsymbol{\pi}_\tau(z_{i,t-1}), \quad i = 1, 2, ..., N, \ t = 1, 2, ..., T, \tag{A.2}$$

where $\boldsymbol{\pi}_\tau(z_{i,t-1}) = [c_0(z_{i,t-1}), c_1(z_{i,t-1}), \ldots, c_\tau(z_{i,t-1})]'$. We now obtain the weights from the standardized kernel

$$w_{it}^{(j)} = \frac{\kappa_b(z_{i,t-1} - \bar{z}_j)}{\sum_{k=1}^{N} \kappa_b(z_{i,t-1} - \bar{z}_k)}. \tag{A.3}$$

where, as in Section 3.2.2, $\kappa_b(\cdot)$ denotes the Gaussian kernel function with bandwidth parameter $b = 1.06\, s_z (NT)^{-1/5}$.

We finally are in a position to construct a smoothed mean group estimator (SMG) of the speed of adjustment coefficient from

$$\hat{\alpha}_{it}^{SMG} = \sum_{j=1}^{N} \hat{\alpha}_{it}^{(j)} w_{it}^{(j)}, \tag{A.4}$$

and the corresponding standard error from

$$\hat{\sigma}_{\alpha,it}^{SMG} = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}\left(\hat{\alpha}_{it}^{(j)} - \hat{\alpha}_{it}^{SMG}\right)^2 w_{it}^{(j)}}. \tag{A.5}$$

B Testing for the Existence of a Long-Run Relationship

To compute the MG, PMG, CPMG and SKMG estimators, we need to be assured that a long-run relation between the dependent variable, y, and the regressors, $\boldsymbol{x}$, in the panel ARDL model exists (unconditionally for MG and PMG, and conditionally for CPMG and SKMG). Presuming that y and $\boldsymbol{x}$ are integrated of order one, I(1), one may test whether they are cointegrated by considering a least squares regression of the form

$$y_{it} = \varpi_i + \boldsymbol{\theta}(\tilde{z}_{i,t-1})'\boldsymbol{x}_{it} + \xi_{it}, \tag{B.1}$$

and examining whether the error term ξ_{it} in this regression is I(0) or I(1). If the null hypothesis is formulated as there being no cointegrating relation between y_{it} and $\boldsymbol{x}_{it}$, then the error term ξ_{it} should be I(1). We employ the panel cointegration test proposed by Westerlund (2005) which implements this idea in a non-parametric format, not relying on specific assumptions regarding the data-generating processes for y_{it} and $\boldsymbol{x}_{it}$. This makes the test applicable both when the conditioning function $\boldsymbol{\theta}(\tilde{z})$ collapses to a constant and when it exhibits variation across different values of $\tilde{z}$. All that is required is that $\boldsymbol{\theta}(\tilde{z})'\boldsymbol{x}$ contains only I(0) and I(1) regressors.

The test also allows for cross-section dependence in the error term, ξ_{it}, via common effects. To test the null hypothesis of no cointegration against the alternative hypothesis of cointegration for all countries, following Westerlund (2005) we compute the following panel variance ratio statistic:

$$VR_P = \left(\sum_{i=1}^{N}\hat{\mathrm{u}}_i\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{\mathrm{v}}_{it}^2, \tag{B.2}$$

where $\hat{\mathrm{v}}_{it} = \sum_{s=1}^{t}\hat{\xi}_{is}$ and $\hat{\mathrm{u}}_i = \sum_{t=1}^{T}\hat{\xi}_{it}^2$. This test statistic is distributed standard Normal under the null hypothesis of no cointegration after appropriate mean and variance corrections as reported by Westerlund (2005).

References

Beveridge, S. and C. Nelson (1981): A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle', *Journal of Monetary Economics*, 7(2), 151–174.

Binder, M., M.H. Pesaran and S. Sharma (2004): Common Features in Exchange Rate Dynamics Using Dynamic Heterogeneous Panel Data Models, Working Paper, Goethe University Frankfurt.

Breitung, J. (2005): A Parametric Approach to the Estimation of Cointegration Vectors in Panel Data, *Econometric Reviews*, 24(2), 151–173.

Cavallo, M. and F. Ghironi (2002): Net Foreign Assets and the Exchange Rate: Redux Revived, *Journal of Monetary Economics*, 49(5), 1057–1097.

Cheung, Y.W., M.D. Chinn and A.G. Pascual (2005): Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?, *Journal of International Money and Finance*, 24(7), 1150–1175.

Cheung, Y.W. and K.S. Lai (2000): On Cross-Country Differences in the Persistence of Real Exchange Rates, *Journal of International Economics*, 50(2), 375–397.

Dornbusch, R. and S. Fischer (1980): Exchange Rates and the Current Account, *American Economic Review*, 70(5), 960–971.

Engel, C., N.C. Mark and K. West (2007): Exchange Rate Models Are Not as Bad as You Think, Working Paper No. 13318, NBER.

Fan, J. and W. Zhang (1999): Statistical Estimation in Varying Coefficient Models, *Annals of Statistics*, 27(5), 1491–1518.

Faruqee, H. (1995): Long-Run Determinants of the Real Exchange Rate: A Stock-Flow Perspective, *IMF Staff Papers*, 42(1), 80–107.

Gagnon, J.E. (1996): Net Foreign Assets and Equilibrium Exchange Rates: Panel Evidence, International Finance Discussion Paper No. 574, Board of Governors of the Federal Reserve System.

Gourinchas, P.O. and H. Rey (2007): International Financial Adjustment, *Journal of Political Economy*, 115(4), 665–703.

Hall, R.E. and C.I. Jones (1999): Why Do Some Countries Produce So Much More Output Per Worker Than Others?, *Quarterly Journal of Economics*, 114(1), 83–116.

Härdle, W. (1990): *Applied Nonparametric Regression*, Cambridge: Cambridge University Press.

Hodrick, R.J. and E.C. Prescott (1997): Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit, and Banking*, 29(1), 1–16.

Kapetanios, G., M.H. Pesaran and T. Yamagata (2011): Panels with Non-Stationary Multifactor Error Structures, *Journal of Econometrics*, 160(2), 326–348.

Krugman, P.R. (1978): Purchasing Power Parity and Exchange Rates, *Journal of International Economics*, 8(3), 397–407.

Kumar, S. and A. Ullah (2000): Semiparametric Varying Parameter Panel Data Models: An Application to Estimation of Speed of Convergence, in: T. B. Fomby and R. Carter Hill (Eds.), *Advances in Econometrics*, Stamford: JAI Press, Vol. 14, pp. 109–128.

Lane, P.R. and G.M. Milesi-Ferretti (2001): The External Wealth of Nations: Measures of Foreign Assets and Liabilities for Industrial and Developing Countries, *Journal of International Economics*, 55(2), 263–294.

Lane, P.R. and G.M. Milesi-Ferretti (2004): The Transfer Problem Revisited: Net Foreign Assets and Real Exchange Rates, *The Review of Economics and Statistics*, 86(4), 841–857.

Lane, P.R. and G.M. Milesi-Ferretti (2007): The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970 – 2004, *Journal of International Economics*, 73(2), 223–250.

Levy-Yeyati, E. and F. Sturzenegger (2005): Classifying Exchange Rate Regimes: Deeds vs. Words, *European Economic Review*, 49(6), 1603–1635.

Mankiw, N.G., D. Romer and D.N. Weil (1992): A Contribution to the Empirics of Economic Growth, *Quarterly Journal of Economics*, 107(2), 407–437.

Offermanns, C.J. and M. Pramor (2007): The CFS International Capital Flow Database: A User's Guide, Working Paper No. 2007/24, Center for Financial Studies.

Pagan, A. and A. Ullah (1999): *Nonparametric Econometrics*, Cambridge: Cambridge University Press.

Pesaran, M.H. (2006): Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure, *Econometrica*, 74(4), 967–1012.

Pesaran, M.H. (2007): A Simple Panel Unit Root Test in the Presence of Cross Section Dependence, *Journal of Applied Econometrics*, 22(2), 265–312.

Pesaran, M.H. and Y. Shin (1999): An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis, in: S. Strom (Ed.), *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, Cambridge: Cambridge University Press.

Pesaran, M.H., Y. Shin and R.P. Smith (1999): Pooled Mean Group Estimation of Dynamic Heterogeneous Panels, *Journal of the American Statistical Association*, 94(446), 621–634.

Pesaran, M.H. and R. Smith (1995): Estimating Long-Run Relationships from Dynamic Heterogeneous Panels, *Journal of Econometrics*, 68(1), 79–113.

Rogoff, K. (1996): The Purchasing Power Parity Puzzle, *Journal of Economic Literature*, 34(2), 647–668.

Sinn, S. (1990): Net External Asset Positions of 145 Countries: Estimation and Interpretation, in: H. Siebert (Ed.), *Kieler Studien*, Tübingen: Mohr, Vol. 234.

Taylor, A.M. and M.P. Taylor (2004): The Purchasing Power Parity Debate, *Journal of Economic Perspectives*, 18(4), 135–158.

Taylor, M.P., D.A. Peel and L. Sarno (2001): Nonlinear Mean-Reversion in Real Exchange Rates: Toward a Solution to the Purchasing Power Parity Puzzles, *International Economic Review*, 42(4), 1015–1042.

Westerlund, J. (2005): New Simple Tests for Panel Cointegration, *Econometric Reviews*, 24(3), 297–316.

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