On the Role of International Capital Flows for Exchange Rate Dynamics: A Dynamic Panel Analysis*

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Abstract

In this paper we revisit medium- to long-run exchange rate determination, focussing on international flows of capital. To do so, we develop a new econometric framework accounting for conditional homogeneity in heterogeneous dynamic panel data models. In particular, in our model the long-run relationship between exchange rates and domestic as well as international prices is a 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, but not outside such environments. We thus argue that the purchasing power parity hypothesis holds conditionally, but not unconditionally, and that international flows of capital and the cumulative stock positions they imply are key to characterizing this conditionality.

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

JEL Classification: F31; F37; C23.

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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 equilibria. Nevertheless, little consensus has been reached. In particular, in the quest to characterize medium- to long-run anchors for the fluctuations of nominal exchange rates, the purchasing power parity (PPP) hypothesis regularly has received support in some studies, yet has been rejected by others. While the differences in empirical findings may in part be attributed to differences in econometric methodology, differences in the samples being analyzed have played a critical role as well.

For research in this area to move forward, it appears essential to view the PPP hypothesis as (at most) conditionally valid and pay close consideration to the interaction between exchange rate fluctuations and the macroeconomic as well as financial environment within which the pricing of currencies occurs. Arguably, the most striking change in this environment over the last couple of decades has been the growth of cross-country capital flows. As argued for example by Lane and Milesi-Ferretti (2005), "financial globalization [has been] one of the key trends that has reshaped the global economy".

In this paper, we study the interaction between medium- to long-run exchange rate dynamics and international flows of capital in the form of equity, foreign direct investment as well as debt. We analyze to what extent the PPP hypothesis can be viewed as an anchor for the pricing of a currency over medium- to long-run horizons *if conditioned* on the international investment position of the country issuing the currency.

Previous work on the PPP hypothesis (for example, Taylor, Peel, and Sarno, 2001 and Binder, Pesaran, and Sharma, 2004) has argued that mean reversion of real exchange rates only occurs under sufficiently large arbitrage opportunities for foreign exchange market participants. Here, we relate these arbitrage opportunities to a country's international investment position: If foreign exchange market participants perceive this investment position to be sufficiently misbalanced to require correction, they expect correction towards a plausible anchor, possibly the level of the real exchange rate predicted by PPP. Such a correction will help to adjust the international investment position both through current account and valuation effects. It also seems likely that under severe imbalances in a country's international investment position foreign exchange market participants will expect reversion to PPP as being insufficient to set off the required correction, and therefore again, as in the absence of sufficiently large arbitrage opportunities, will pay limited – if any – attention to PPP.

We test these hypotheses in this paper and more generally provide a characterization of the role of international capital flows for medium- to long-run exchange rate dynamics using a panel of 71 countries over the time period 1970 to 2004. We propose and develop 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 models in the literature, our model explicitly distinguishes between short- and long-run dynamics, does not impose exogeneity restrictions on the price and exchange rate series, is valid in the presence of unit roots in these series, and allows for heterogeneous short-run dynamics of prices and exchange rates across countries. It moves beyond the models presently available in the literature by introducing *conditional* commonality across countries in the long-run relation (where the conditioning in this paper is with respect to measures of the international investment position). We propose to 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 semi-parametrically using local kernels (resulting in what we call the state kernel mean group (SKMG) panel model).

Our main empirical results are as follows: We find rather strong support for the PPP hypothesis in environments of limited negative net foreign asset to GDP positions. 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, and equally important, the speed of adjustment towards the long-run relation is, in light of the estimates typically obtained in the literature, surprisingly fast, at less than two years half-life for shocks to the PPP relation. We also find that in environments of large negative, zero or positive net foreign asset to GDP positions the PPP hypothesis does not provide a relevant medium- to long-run anchor for the pricing of currencies. We finally find that our results are unlikely to be driven by some other features of the macroeconomic and financial environment rather than the international investment position of a country, and in particular not by the country's exchange rate regime or its average degree of price stability.

The 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 dynamic cross-country panel models. We outline the main features of our newly assembled data base on international capital flows in Section 3 of the paper. Section 4 develops the conditional pooled mean group and state kernel mean group panel models. Our empirical findings are presented in Section 5, and Section 6 concludes and discusses directions for future research. Four appendices provide details on the assembly of our data set and on aspects of our econometric methodology.

2 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 fluctuations and the macroeconomic as well as financial environment within which the pricing of currencies occurs. Two of the exceptions are Taylor, Peel, and Sarno (2001) and Binder, Pesaran, and Sharma (2004). The former proposed a nonlinear model for the interaction of exchange rates and domestic as well as foreign prices, capturing that mean reversion of real exchange rates would only occur if they deviated sufficiently strongly from the PPP anchor. The latter argued – using dynamic panel models subject to simple sample splits – that the empirical validity of the purchasing power parity hypothesis is linked to the volatility of prices, and that below a certain minimum threshold of price volatility arbitrage opportunities would be too small for PPP to hold.

Neither of these papers considered the link between exchange rate determination on the one hand and international capital flows and their impact on a country's international investment position on the other hand. Important papers investigating this link empirically include Lane and Milesi-Ferretti (2004) and Cheung, Chinn, and Pascual (2005). Both of these papers consider a country's net foreign asset position as one of the determinants of the equilibrium real exchange rate. However, both papers constrain themselves to rather simple econometric specifications, not allowing for a panel specification separating heterogeneous short-run dynamics from (conditionally) homogeneous long-run relations.

[1] For a review see, for example, Sarno and Taylor (2002).

2.2 Dynamic Panel and Varying Coefficient Models

Key to the understanding of the development of the recent econometric literature on cross-country dynamic panel data models is the result by Pesaran and Smith (1995) that if the model's slope coefficients vary across countries, whether randomly or systematically, then the means of the coefficients cannot be estimated consistently using a dynamic panel model imposing 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 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 mean group estimator has the drawback of not allowing for any efficiency gains of working with panel (rather than time-series) data that are feasible when some features are common across countries. While short-run dynamics are rather unlikely to share common features across a broad set of countries, common features are most likely to be present in long-run equilibrium relationships. This insight is exploited in the pooled mean group (PMG) estimator of Pesaran, Shin, and Smith (1999), which imposes homogeneity of the slope coefficients in the long-run equilibrium relationships, but unrestricted heterogeneity of the coefficients characterizing the short-run dynamics.

The dynamic panel model we develop in this paper addresses situations where the homogeneity of the slope coefficients in the long-run equilibrium relationships does not hold unconditionally, but rather is tied to certain features of the economic environment. In such settings, the pooled mean group estimator would yield inconsistent estimates of the long-run slope coefficients, while the mean group estimator would still suffer from (as we shall see) important lack of efficiency.

3 International Capital Flow Data

Our data set comprises data on international assets and liabilities, both flow and stock data, for a total of 153 countries over the time period 1970 to 2004. We obtained most of the flow data from the Balance of Payments Statistics (BOPS); stock data were taken from the International Investment Position (IIP) data base. Both data bases are incorporated in the International Financial Statistics (IFS) maintained by the International Monetary Fund (IMF). All international capital data we used were compiled in millions of U.S. Dollars.

In addition to international capital flows and stocks, we have collected data on gross domestic product (GDP) from the World Bank's World Development Indicators database,[2] bilateral nominal exchange rates and prices from the IFS, as well as exports and imports which are taken from the Direction of Trade Statistics maintained by the IMF.

Our basis for computing the net foreign asset (NFA) position of a country is the accounting identity underlying the balance of payments: Given an initial estimate for the stock of NFA, subsequent stocks can be assessed by cumulating current account balances, taking valuation changes in the stock into account as well. Summarizing net valuation changes in ΔNV, we obtain the stock of net foreign assets as

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

where CA_{it} denotes country i's current account balance at time t and KA_{it} refers to its capital account balance.[3] The sources of valuation changes differ across types of financial assets and liabilities. In particular, we adjust portfolio equity investment liabilities using domestic stock market indices (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 adjust foreign direct investment (FDI) liabilities using bilateral real exchange rates relative to the U.S., and FDI assets using an effective real exchange rate index.[4] Changes in the value of international reserve assets are obtained from the difference between flows and the change in the corresponding stock value. See Appendix A for further details.

When flow data are accumulated to obtain stocks, they have to be initialized with an existing stock figure for some reference period. For the adjusted cumulative current account, 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. We initialized various subcomponents of NFA using existing stock data from the IIP database. Given that the flow data may have an earlier starting point than the stock data, occasionally we needed to backcast the

[2] 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.

[3] 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.

[4] Throughout this paper we use effective exchange rates computed using trade weights (see also Appendix A). While a mixture of trade and capital weights might be most appealing, to incorporate capital weights we would need information on *bilateral* flows of capital that for the set of countries we consider (or even a substantial sub-sample thereof) at present is not available.

initial value. In effect, our cumulative flow figures are thus anchored by the first available stock figure from IIP data. Consequently, we did not compute cumulative flow figures if they did not overlap with corresponding stock data.

Since we completed compilation of our data set, Lane and Milesi-Ferretti (2006) have augmented the international capital flow data set described in Lane and Milesi-Ferretti (2001); the new version now has similar cross-country and time coverage as our data set. In contrast to Lane and Milesi-Ferretti (2006), our database also separately reports the valuation effects. For more details on the construction of our data set, see Offermanns and Pramor (2006).

4 Econometric Methodology

4.1 The Mean Group and Pooled Mean Group Approaches

We begin by reviewing the dynamic panel models on which our proposed models do build: the mean group and pooled mean group approaches. As in Pesaran, Shin, and Smith (1999), let us consider the following panel version of an autoregressive distributed lag, ARDL(p,q), model:

$$y_{it} = \varpi_i + \sum_{j=1}^{p} \rho_{ij} y_{i,t-j} + \sum_{j=0}^{q} \boldsymbol{\varrho}'_{ij} \boldsymbol{x}_{i,t-j} + u_{it}, \tag{2}$$

where $i = 1, 2, \ldots, N$ indexes countries, $t = 1, 2, \ldots, T_i$ stands for time periods, y_{it} denotes the dependent variable (with coefficients ρ_{ij} on its lagged values), ϖ_i represents the country-specific intercept term, and $\boldsymbol{x}_{it}$ and $\boldsymbol{\varrho}_{ij}$ represent $(k \times 1)$ vectors of explanatory variables and coefficients, respectively.[5] We assume that $\min_i(T_i)$ is sufficiently large so that the ARDL model in (2) can be separately estimated for each country.

As is now widely recognized in the cross-country dynamic panel literature, it is important to allow for cross-sectional correlation of the error terms. Let us therefore specify u_{it} as:

$$u_{it} = \boldsymbol{\lambda}'_i \boldsymbol{f}_t + \varepsilon_{it}, \tag{3}$$

[5] For notational simplicity, we denote the lag orders by p and q, respectively, although in our empirical implementation we allow for these to differ across variables and countries, that is, work with the model specification

$$y_{it} = \varpi_i + \sum_{j=1}^{p_i} \rho_{ij} y_{i,t-j} + \sum_{l=1}^{k} \sum_{j=0}^{q_{li}} \varrho_{li,j} x_{li,t-j} + u_{it}.$$

such that the source of 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 $\boldsymbol{\lambda}_i$. The remaining 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 are modelled as unobservable, we can control for these by augmenting the ARDL model (2) with cross-sectional averages of the model variables following the correlated effects augmentation (CEA) methodology of Pesaran (2006a): Averaging (2) across i under uncorrelatedness of slope coefficients and regressors, one obtains

$$\bar{y}_t = \bar{\varpi} + \sum_{j=1}^{p} \bar{\rho}_j \bar{y}_{t-j} + \sum_{j=0}^{q} \bar{\boldsymbol{\varrho}}_j' \bar{\boldsymbol{x}}_{t-j} + \bar{\boldsymbol{\lambda}}' \boldsymbol{f}_t + \bar{\varepsilon}_t. \tag{4}$$

Since the error component ε_{it} is independently distributed across i and t by assumption, $\bar{\varepsilon}_t$ tends to zero in root mean square error as N becomes large. The cross-sectional correlation of u_{it} can therefore be captured through a linear combination of the cross-sectional averages of the dependent variable and all regressors:

$$\boldsymbol{\lambda}_i' \boldsymbol{f}_t = \kappa_i \bar{\boldsymbol{\lambda}}' \boldsymbol{f}_t = \eta_i \bar{y}_t + \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}_t + \sum_{j=0}^{p-1} \eta_{ij} \Delta \bar{y}_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\zeta}_{ij}' \Delta \bar{\boldsymbol{x}}_{t-j} - \kappa_i \bar{\varpi} \tag{5}$$

with reparameterizations $\eta_i = \kappa_i(1 - \sum_{j=1}^{p} \bar{\rho}_j)$, $\boldsymbol{\zeta}_i = \kappa_i(\sum_{j=0}^{q} \bar{\boldsymbol{\varrho}}_j)$, $\eta_{ij} = \kappa_i(\sum_{l=j+1}^{p} \bar{\rho}_l)$ and $\boldsymbol{\zeta}_{ij} = \kappa_i(\sum_{l=j+1}^{q} \bar{\boldsymbol{\varrho}}_j)$ for some κ_i. Using Equation (5), the error-correction representation of the panel ARDL model (2) and (3) can be written as:

$$\begin{aligned} \Delta y_{it} = \mu_i + \alpha_i y_{i,t-1} + \boldsymbol{\beta}_i' \boldsymbol{x}_{it} + \sum_{j=1}^{p-1} \phi_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}_{ij}' \Delta \boldsymbol{x}_{i,t-j} \\ + \eta_i \bar{y}_t + \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}_t + \sum_{j=0}^{p-1} \eta_{ij} \Delta \bar{y}_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\zeta}_{ij}' \Delta \bar{\boldsymbol{x}}_{t-j} + \varepsilon_{it}, \end{aligned} \tag{6}$$

with $\mu_i \equiv \varpi_i - \kappa_i \bar{\varpi}$, $\alpha_i \equiv -(1 - \sum_{j=1}^{p} \rho_{ij})$, $\boldsymbol{\beta}_i \equiv \sum_{j=0}^{q} \boldsymbol{\varrho}_{ij}$ and $\phi_{ij} \equiv -\sum_{m=j+1}^{p} \rho_{im}$, $\boldsymbol{\delta}_{ij} \equiv -\sum_{m=j+1}^{q} \boldsymbol{\varrho}_{im}$.

From (6) the long-run relationship between y and $\boldsymbol{x}$ is given by

$$\hat{y}_{it} = -\alpha_i^{-1} \boldsymbol{\beta}_i' \boldsymbol{x}_{it} - \alpha_i^{-1}(\eta_i \bar{y}_t + \boldsymbol{\zeta}_i' \bar{\boldsymbol{x}}_t) - \alpha_i^{-1} \mu_i \equiv \boldsymbol{\theta}_i' \boldsymbol{x}_{it} + \chi_{it} + \omega_i, \tag{7}$$

where χ_{it} represents the common effect in the equilibrium level of y_{it}.

The long-run elasticities between y_i and $\boldsymbol{x}_i$ given by $\boldsymbol{\theta}_i$ and the speed of adjustment towards the long-run relation for country i given by α_i constitute the key coefficients of economic interest. In what follows, we will therefore also work with a transformed version of the model in (6). We define the equilibrium error, ξ_{it}, as follows:

$$\xi_{it}(\boldsymbol{\theta}_i) = y_{i,t-1} - \boldsymbol{\theta}_i'\boldsymbol{x}_{it} - \omega_i, \tag{8}$$

and we multiply Equation (6) with a matrix $\boldsymbol{M}_i$ such that

$$\boldsymbol{M}_i\Delta\boldsymbol{y}_i = \alpha_i(\boldsymbol{M}_i\boldsymbol{y}_{i,-1} - \boldsymbol{M}_i\boldsymbol{X}_i\boldsymbol{\theta}_i) + \boldsymbol{\varepsilon}_i = \alpha_i\boldsymbol{M}_i\boldsymbol{\xi}_i(\boldsymbol{\theta}_i) + \boldsymbol{\varepsilon}_i, \tag{9}$$

where for notational convenience we have stacked all variables in the time dimension for each country, such that $\Delta\boldsymbol{y}_i = (\Delta y_{i1}\ \Delta y_{i2}\ \dots\ \Delta y_{iT})'$, $\boldsymbol{y}_{i,-1} = (y_{i,0}\ y_{i,1}\ \dots\ y_{i,T-1})'$, $\boldsymbol{X}_i = (\boldsymbol{x}_{i1}\ \boldsymbol{x}_{i2}\ \dots\ \boldsymbol{x}_{iT})'$, $\boldsymbol{\xi}_i(\boldsymbol{\theta}_i) = [\xi_{i1}(\boldsymbol{\theta}_i)\ \xi_{i2}(\boldsymbol{\theta}_i)\ \dots\ \xi_{iT}(\boldsymbol{\theta}_i)]'$, and $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}\ \varepsilon_{i2}\ \dots\ \varepsilon_{iT})'$. The idempotent matrix $\boldsymbol{M}_i$ captures the country-specific least-squares estimators of the extracted coefficients and is defined as

$$\boldsymbol{M}_i \equiv \boldsymbol{I}_{T_i} - \boldsymbol{H}_i(\boldsymbol{H}_i'\boldsymbol{H}_i)^{-1}\boldsymbol{H}_i', \tag{10}$$

where $\boldsymbol{I}_{T_i}$ denotes the identity matrix and $\boldsymbol{H}_i$ summarizes the extracted regressors, including lagged differences, cross-sectional averages and deterministic variables,

$$\boldsymbol{H}_i \equiv (\boldsymbol{h}_{i1}\ \ \boldsymbol{h}_{i2}\ \ \dots\ \ \boldsymbol{h}_{i,T})', \tag{11}$$

with

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

The Pesaran and Smith (1995) mean group (MG) estimators of α_i and $\boldsymbol{\theta}_i$ are obtained by least squares estimation of (9) for each country separately and then averaging the country-specific coefficient estimates. Standard errors for these mean group 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) pooled mean group (PMG) estimation of the panel ARDL model is to assume that the long-run coefficients $\boldsymbol{\theta}_i$ are homogeneous across all countries (that is, $\boldsymbol{\theta}_i = \boldsymbol{\theta},\ i = 1, 2, \dots, N$), but that all other coefficients are still allowed to differ in unrestricted fashion across countries. To obtain the PMG estimator thus is based on numerical maximization of the corresponding likelihood function.

4.2 Panel Cointegration Test

Presuming that y_{it} and $\boldsymbol{x}_{it}$ are integrated of order one, I(1), one may test whether they are cointegrated by considering a least squares regression of the form

$$y_{it} = \omega_i + \boldsymbol{\theta}_i' \boldsymbol{x}_{it} + \xi_{it}, \tag{12}$$

and testing 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). In this paper, we employ the panel cointegration test proposed by Westerlund (2005) which implements this idea in a nonparametric format, not relying on specific assumptions regarding the data-generating processes for y_{it} and $\boldsymbol{x}_{it}$. In particular, the test also allows for cross-section dependence in the equilibrium error, 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:

$$VR_P = \left(\sum_{i=1}^{N} \hat{r}_i \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{e}_{it}^2, \tag{13}$$

where $\hat{e}_{it} = \sum_{s=1}^{t} \hat{\xi}_{is}$ and $\hat{r}_i = \sum_{t=1}^{T} \hat{\xi}_{it}^2$. This test statistic is distributed standard normal under the null hypothesis of no cointegration under appropriate mean and variance corrections as reported by Westerlund (2005). In Section 5, we also report values for a second test statistic, VR_G, that tests the null hypothesis of no cointegration against the alternative hypothesis of cointegration for N_c countries, where $\lim_{N \to \infty} N_c/N \to \delta > 0$.

4.3 Conditionally Homogeneous Long-Run Equilibria

Having assured the existence of a long-run relation between y_{it} and $\boldsymbol{x}_{it}$, the pooled mean group estimator has considerable intuitive 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 any strong common features across countries – they are thus left as heterogeneous. At the same time, the PPP hypothesis imposes a common restriction across countries on the long-run coefficients.

As we have argued in the Introduction, though, it still 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 and what may be the most relevant determinant of the international macroeconomic and financial environment, we propose conditioning the long-run equilibrium on the state of each country's international investment position.

Denoting the value of this state in period t in country i by $\tilde{z}_{it}$ (in our empirical analysis a moving average of some measure z_{it} of the country's international investment position – more details on this in Section 5 below)[6], we therefore propose the following augmented panel ARDL model:

$$\Delta y_{it} = \mu_i + \alpha_i(\tilde{z}_{it})[y_{i,t-1} - \boldsymbol{\theta}(\tilde{z}_{it})'\boldsymbol{x}_{it}] + \sum_{j=1}^{p-1} \phi_{ij}(\tilde{z}_{it})\Delta y_{i,t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}_{ij}(\tilde{z}_{it})'\Delta \boldsymbol{x}_{i,t-j}$$
$$+ \eta_i(\tilde{z}_{it})\bar{y}_t + \boldsymbol{\zeta}_i(\tilde{z}_{it})'\bar{\boldsymbol{x}}_t + \sum_{j=0}^{p-1} \eta_{ij}(\tilde{z}_{it})\Delta \bar{y}_{t-j} + \sum_{j=0}^{q-1} \boldsymbol{\zeta}_{ij}(\tilde{z}_{it})'\Delta \bar{\boldsymbol{x}}_{t-j} + \varepsilon_{it}. \quad (14)$$

Note that all short-run coefficients in (14) are a function of both $\tilde{z}_{it}$ as well as other country-specific characteristics (reflected in the i subscripts for all coefficient functionals), but that the long-run coefficients are specified as a homogeneous function across countries of the state variable $\tilde{z}_{it}$. We pursue two different approaches to modelling the conditional functions. One is parametric and uses flexible form polynomials, the other one is nonparametric and uses local kernels.

4.3.1 Parametric Approach: Conditional Pooled Mean Group (CPMG) Estimation

Our first approach to capturing the dependence of the long-run coefficients on the state variable $\tilde{z}_{it}$ is to specify $\boldsymbol{\theta}(\tilde{z}_{it})$ using a homogeneous parametric function of flexible form, for example Chebyshev polynomials as one specification of orthogonal polynomials.[7] In particular, we specify the long-run coefficients as

$$\boldsymbol{\theta}(\tilde{z}_{it}) = \sum_{s=0}^{\tau} \boldsymbol{\gamma}_s^{(\theta)} \cdot c_s(\tilde{z}_{it}), \quad (15)$$

where the Chebyshev polynomials may be recursively defined as

$$c_{s+1}(\tilde{z}_{it}) = 2\tilde{z}_{it} c_s(\tilde{z}_{it}) - c_{s-1}(\tilde{z}_{it}), \quad s \geq 1,$$

[6]In this paper, we specify $\tilde{z}_{it}$ 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.

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

with $c_0(\tilde{z}_{it}) = 1$ and $c_1(\tilde{z}_{it}) = \tilde{z}_{it}$, and where $\boldsymbol{\gamma}_s^{(\theta)}$ is a k-dimensional vector of homogeneous coefficients. The coefficient functionals $\alpha_i(\tilde{z}_{it})$, $\phi_{ij}(\tilde{z}_{it})$ etc. can be specified in similar form (albeit with country-specific rather than homogeneous coefficients). We propose to call this model the *conditional pooled mean group* (CPMG) model.

One approach to the estimation of the CPMG model is to concentrate the likelihood function, writing it as a function of $\alpha_i(\tilde{z}_{it})$ and $\boldsymbol{\theta}(\tilde{z}_{it})$ only, and subsequently maximize this concentrated likelihood function. An alternative is to adapt the two-step estimation strategy proposed by Breitung (2005) for the PMG model to our CPMG model: Estimate in a first step the parameters in (14) (including σ_i^2) from

$$\Delta \boldsymbol{y}_i = \boldsymbol{\mathcal{Y}}_{i,-1}(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\alpha)} + \boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta)} + \boldsymbol{\mathcal{H}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\psi)} + \boldsymbol{\varepsilon}_i, \tag{16}$$

where $\boldsymbol{\mathcal{Y}}_{i,-1}(\tilde{\boldsymbol{z}}_i)$, $\boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)$, and $\boldsymbol{\mathcal{H}}_i(\tilde{\boldsymbol{z}}_i)$ are combinations of $\boldsymbol{y}_{i,-1}$, $\boldsymbol{x}_i$, and $\boldsymbol{h}_i$, respectively, with the Chebyshev polynomials, and $\boldsymbol{\gamma}_i^{(\alpha)}$, $\boldsymbol{\gamma}_i^{(\beta)}$, and $\boldsymbol{\gamma}_i^{(\psi)}$ are the polynomial coefficients. For a detailed description of the matrices of coefficients and variables involved see Appendix B. In a second step, estimate the long-run relationship through pooled least-squares estimation of

$$\boldsymbol{v}_i = -\boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}^{(\theta)} + \boldsymbol{\nu}_i, \tag{17}$$

where

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

and

$$V(\boldsymbol{\nu}_i) = \hat{\boldsymbol{A}}_i(\tilde{\boldsymbol{z}}_i)^{-2}\hat{\sigma}_i^2,$$

with $\boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i) = \mathrm{diag}[\alpha_i(\tilde{z}_{i1}), \alpha_i(\tilde{z}_{i2}), \ldots, \alpha_i(\tilde{z}_{iT})]$. In practice, to keep the model structure parsimonious one may wish to restrict the orders of most polynomials in (14) (except for those in $y_{i,t-1}$ and $\boldsymbol{x}_{it}$) to zero. Note that such a restriction is completely consistent with the idea of unrestricted heterogeneity of the short-run dynamics.

Due to the heterogeneous nature of the functional relationship between α_i and the conditioning variable $\tilde{z}_{it}$, we need to be explicit about the computation of the speed of adjustment coefficient at each observation (i, t). For each $\tilde{z}_{it}$ we compute the average across all functionals $\alpha_j(\tilde{z}_{it})$, $j = 1, 2, ..., N$, incorporating in the averaging procedure a weighting with respect to the local environment for which each functional α_j has been estimated. The details of the procedure we use to compute a smoothed mean group estimate and its corresponding standard error are laid out in Appendix C.

4.3.2 Semi-Parametric Approach: State Kernel Mean Group (SKMG) Estimation

Our second approach to capturing the interdependence between the long-run coefficients and the state variable $\tilde{z}_{it}$ is to model this through a non-parametric kernel, building on the work of Kumar and Ullah (2000). Such a kernel will serve the purpose of including only those observations in the estimation of a parameter that are relevant at the specified level of the underlying state variable $\tilde{z}_{it}$. This is done by weighting all available observations using a kernel function and minimizing a modified residual sum of squares

$$\hat{\wp}(\tilde{z}_{js}) = \underset{\wp(\tilde{z}_{js})}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \varepsilon_{it}^2 k(\tilde{z}_{it} - \tilde{z}_{js}), \qquad j = 1, 2, \ldots, N, \quad s = 1, 2, \ldots, T_i, \qquad (18)$$

where $\wp(\tilde{z}_{js}) = [\alpha(\tilde{z}_{js})\ \boldsymbol{\beta}(\tilde{z}_{js})'\ \boldsymbol{\psi}_1(\tilde{z}_{js})'\ \boldsymbol{\psi}_2(\tilde{z}_{js})'\ \ldots\ \boldsymbol{\psi}_N(\tilde{z}_{js})']'$, and $k(\tilde{z}_{it} - \tilde{z}_{js})$ represents the kernel that effectively gives high weight to observations "close" to $\tilde{z}_{js}$ and low weight to observations "far" from this point.

Again adhering to the principle of parsimony and only incorporating kernels for the coefficients of $y_{i,t-1}$ and $\boldsymbol{x}_{it}$, the concentrated linear[8] version of our panel ARDL model in error-correction representation, (14), stacked in time dimension, becomes:

$$\Delta \boldsymbol{y}_i^* = \boldsymbol{y}_{i,-1}^* \alpha(\tilde{z}_{js}) + \boldsymbol{X}_i^* \boldsymbol{\beta}(\tilde{z}_{js}) + \boldsymbol{\varepsilon}_i, \qquad j = 1, 2, \ldots, N, \quad s = 1, 2, \ldots, T_i. \qquad (19)$$

with $\Delta \boldsymbol{y}_i^* = \boldsymbol{M}_i \Delta \boldsymbol{y}_i$, $\boldsymbol{y}_{i,-1}^* = \boldsymbol{M}_i \boldsymbol{y}_{i,-1}$, and $\boldsymbol{X}_i^* = \boldsymbol{M}_i \boldsymbol{X}_i$. Taking account of heteroskedastic variances σ_i^2, Equation (18) can be solved using the Local Least Squares Kernel (LLSK) estimator,

$$\hat{\boldsymbol{\varphi}}(\tilde{z}_{js}) = [\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(\tilde{z}_{js})\boldsymbol{W}]^{-1}\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(\tilde{z}_{js})\Delta \boldsymbol{y}^*, \quad j = 1, 2, \ldots, N,\ s = 1, 2, \ldots, T_i, \quad (20)$$

where

$$\boldsymbol{\varphi}(\tilde{z}_{js}) = \left[\alpha(\tilde{z}_{js})\ \boldsymbol{\beta}(\tilde{z}_{js})'\right]',$$

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

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

with $\Delta \boldsymbol{y}^* = (\Delta \boldsymbol{y}_1^{*\prime}\ \Delta \boldsymbol{y}_2^{*\prime} \ldots \Delta \boldsymbol{y}_N^{*}{}')'$, $\boldsymbol{y}_{-1}^* = (\boldsymbol{y}_{1,-1}^*{}'\ \boldsymbol{y}_{2,-1}^*{}'\ \ldots\ \boldsymbol{y}_{N,-1}^*{}')'$, and $\boldsymbol{X}^* = (\boldsymbol{X}_1^{*\prime}\ \boldsymbol{X}_2^{*\prime}\ \ldots\ \boldsymbol{X}_N^*{}')'$. $\boldsymbol{K}(\tilde{z}_{js})$ is the diagonal matrix containing the values of $k(\tilde{z}_{it} - \tilde{z}_{js})$; for its actual shape see Appendix D. The variance matrix $\boldsymbol{\Omega}$ is defined as

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

[8]Note that we work with $\boldsymbol{\beta}_i(\tilde{z}_{it})$ (rather than $\boldsymbol{\theta}(\tilde{z}_{it})$) for the specification of the kernel.

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

$$V[\hat{\boldsymbol{\varphi}}(\tilde{z}_{js})] = [\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(\tilde{z}_{js})\boldsymbol{W}]^{-1}\boldsymbol{W}'\boldsymbol{\Omega}_1^{-1}(\tilde{z}_{js})\boldsymbol{W}[\boldsymbol{W}'\boldsymbol{\Omega}^{-1}(\tilde{z}_{js})\boldsymbol{W}]^{-1} \tag{21}$$

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

To allow for richer patterns of parameter variation across states than regarded by the LLSK estimator, we add polynomials of higher order as employed by Fan and Zhang (1999). To incorporate those in the computation of the local coefficients, we again employ Chebyshev polynomials. As a consequence, we modify the regressors in (20) in the following way:

$$\tilde{\boldsymbol{W}}(\tilde{z}_{js}) = [\tilde{\boldsymbol{w}}_{11}(\tilde{z}_{js}) \;\; \tilde{\boldsymbol{w}}_{12}(\tilde{z}_{js}) \;\; \ldots \;\; \tilde{\boldsymbol{w}}_{NT}(\tilde{z}_{js})]', \tag{22}$$

where

$$\tilde{\boldsymbol{w}}_{it}(\tilde{z}_{js}) = [\tilde{\boldsymbol{w}}'_{1,it}(\tilde{z}_{js}) \;\; \tilde{\boldsymbol{w}}'_{2,it}(\tilde{z}_{js}) \;\; \ldots \;\; \tilde{\boldsymbol{w}}'_{k+1,it}(\tilde{z}_{js})]', \tag{23}$$

and

$$\begin{aligned} \tilde{\boldsymbol{w}}'_{l,it}(\tilde{z}_{js}) &= w_{l,it}\; [c_0(\tilde{z}_{it}-\tilde{z}_{js}) \;\; c_1(\tilde{z}_{it}-\tilde{z}_{js}) \;\; c_2(\tilde{z}_{it}-\tilde{z}_{js}) \;\; \ldots \;\; c_\tau(\tilde{z}_{it}-\tilde{z}_{js})] \\ &= w_{l,it}\; \boldsymbol{\pi}'_\tau(\tilde{z}_{it}-\tilde{z}_{js}), \quad l = 1,2,\ldots,k+1. \end{aligned} \tag{24}$$

Note that $w_{l,it}$ refers to observation (i,t) for the l-th variable in $\boldsymbol{W}$.

The resulting estimator $\tilde{\boldsymbol{\varphi}}_l(\tilde{z}_{js})$ can be used to construct local estimates of $\varphi_l(\tilde{z}_{js})$ as

$$\hat{\varphi}_l(\tilde{z}_{js}) = \frac{\sum_{i=1}^N \sum_{t=1}^T \boldsymbol{\pi}'_\tau(\tilde{z}_{js}-\tilde{z}_{it})\tilde{\boldsymbol{\varphi}}_l(\tilde{z}_{it})k(\tilde{z}_{js}-\tilde{z}_{it})}{\sum_{i=1}^N \sum_{t=1}^T k(\tilde{z}_{js}-\tilde{z}_{it})}, \quad l = 1,2,\ldots,k+1, \tag{25}$$

and

$$V[\hat{\varphi}_l(\tilde{z}_{js})] = \frac{\sum_{i=1}^N \sum_{t=1}^T \boldsymbol{\pi}'_\tau(\tilde{z}_{js}-\tilde{z}_{it})V[\tilde{\boldsymbol{\varphi}}_l(\tilde{z}_{it})]\boldsymbol{\pi}_\tau(\tilde{z}_{js}-\tilde{z}_{it})k(\tilde{z}_{js}-\tilde{z}_{it})}{\sum_{i=1}^N \sum_{t=1}^T k(\tilde{z}_{js}-\tilde{z}_{it})}, \quad l = 1,2,\ldots,k+1. \tag{26}$$

We call this approach the *state kernel mean group* (SKMG) method.

5 Empirical Results

5.1 Data and Model Specification

While our data set contains annual observations on a total of 153 countries, for the empirical analysis of this paper we restrict attention to 71 countries only. These countries were selected on the basis of the following criteria:

1. At least 25 consecutive time-series observations being available for all variables entering our analysis;

2. population size of at least one million in 1970 (according to the World Bank's World Development Indicators, complemented by data from the Penn World Tables);

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

4. economy not a major oil producer (based on the classification from Mankiw, Romer, and Weil, 1992).

The resulting set of 71 countries included in our analysis is as follows:

- *20 industrial countries*: Australia, Austria, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States;

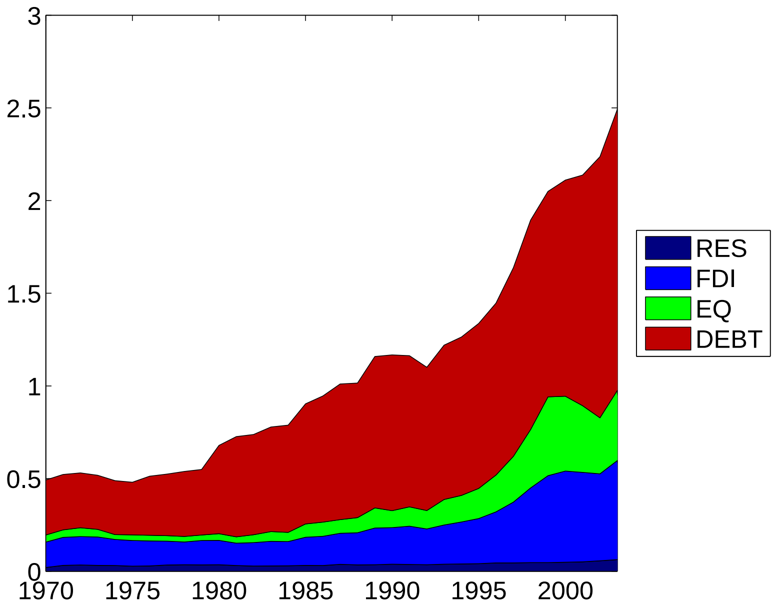
- *12 emerging markets*: Argentina, Chile, Costa Rica, Israel, Libya, Malaysia, Mexico, Panama, Singapore, Turkey, Uruguay, Venezuela;

- *39 developing countries* : Algeria, Bolivia, Brazil, Burkina Faso, Cameroon, Central African Republic, Colombia, Côte d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Ghana, Guatemala, Haiti, Honduras, India, Jamaica, Jordan, Kenya, Madagascar, Malawi, Morocco, Myanmar, Niger, Nigeria, Pakistan, Papua New Guinea, Paraguay, Peru, Philippines, Senegal, Sierra Leone, Sri Lanka, Sudan, Syrian Arab Republic, Thailand, Togo, Uganda.

Figure 1 summarizes the development of the sum of gross asset and liability stocks as a ratio to GDP for our sample over the time period 1970 to 2003.[9] The figure mirrors the global trend of increasing international financial integration that has led to a massive build-up of international capital positions.

[9] Data points for 2004 are only scarcely available such that they would severely distort the representation of the international financial environment for that year.

Figure 1: Sum of Gross Asset and Liability Stocks as a Ratio to GDP, 1970–2003



Notes: Aggregation across countries of absolute values for assets and liabilities of the categories reserve assets, FDI, equity and debt, divided by aggregate GDP.

We consider the following panel ARDL model (in error-correction representation):

$$\Delta e_{it} = \mu_i + \alpha_i(\tilde{z}_{it}) \left[e_{i,t-1} - \boldsymbol{\theta}_i(\tilde{z}_{it})' \begin{pmatrix} p_{it} \\ p^*_{it} \end{pmatrix} \right] + \eta_i \bar{e}_t + \zeta_i(\bar{p}_t - \bar{p}^*_t)$$
$$+ \sum_{j=1}^{p_i-1} \phi_{ij} \Delta e_{i,t-j} + \sum_{j=0}^{q_{i1}-1} \delta_{1,ij} \Delta p_{i,t-j} + \sum_{j=0}^{q_{i2}-1} \delta_{2,ij} \Delta p^*_{i,t-j}$$
$$+ \sum_{j=0}^{p_i-1} \eta_{ij} \Delta \bar{e}_{t-j} + \sum_{j=0}^{\max(q_{1i},q_{2i})-1} \zeta_{ij}(\Delta \bar{p}_{t-j} - \Delta \bar{p}^*_{t-j}) + \varepsilon_{it}, \tag{27}$$

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, p^*_{it} the logarithm of weighted foreign consumer prices (using the same weighting scheme as for the effective exchange rate); the period-t cross-sectional averages of each of these variables are denoted by $\bar{e}_t$, $\bar{p}_t$ and $\bar{p}^*_t$, respectively. The state variable $\tilde{z}_{it}$ is specified as a moving average of the net foreign asset to GDP ratio over the previous ten years in the sample. The parameters of principal interest to us are the long-run coefficients $\boldsymbol{\theta}_i(\tilde{z}_{it}) = [\theta_{1i}(\tilde{z}_{it}), \theta_{2i}(\tilde{z}_{it})]'$ and the speed of adjustment parameter $\alpha_i(\tilde{z}_{it})$.

Note that (unconditional) PPP implies that $\theta_{1i} = 1$ and $\theta_{2i} = -1$. By conditioning the coefficients on $\tilde{z}_{it}$, we render these dependent on the country's international investment position.

For MG estimation of our model, we set $\alpha_i(\tilde{z}_{it}) = \alpha_i$ and $\boldsymbol{\theta}_i(\tilde{z}_{it}) = \boldsymbol{\theta}_i$. For PMG estimation, we set $\alpha_i(\tilde{z}_{it}) = \alpha_i$ and $\boldsymbol{\theta}_i(\tilde{z}_{it}) = \boldsymbol{\theta}$. For CPMG estimation, we set $\boldsymbol{\theta}_i(\tilde{z}_{it}) = \boldsymbol{\theta}(\tilde{z}_{it})$; $\alpha_i(\tilde{z}_{it})$ and $\boldsymbol{\theta}(\tilde{z}_{it})$ are specified to be first-order 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 $\boldsymbol{\theta}_i$ (via $\boldsymbol{\beta}_i$). Lag orders are selected on the basis of both the Akaike Information Criterion (AIC) and the Schwartz Bayesian Criterion (SBC).

In addition to the international investment position of a country, it is likely that its medium- to long-run exchange rate is also influenced by other features of its macroeconomic and financial environment such as its exchange rate regime or its inflation record. The incorporation of such additional factors in a multivariate CPMG or SKMG model would be desirable. However, in the current setup this would overly increase the parameter space to be estimated. In this paper, we confine ourselves to analyzing such additional factors by means of sample splits. To consider the role of exchange rate regimes, 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 a five-way categorization of the exchange rate regimes of up to 183 countries as "flexible", "dirty float", "inconclusive", "crawling peg", and "fixed". We recode these categories to numbers one to five according to this order. 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.

Our sample split constructs two groups of countries: The first group consists of countries whose average exchange rate classification code is at most equal to three, the second group features an average classification code of above three.

We capture the impact of a country's inflation record in splitting our sample into a group comprising countries with an average inflation rate exceeding 8% (which we call "high inflation countries") as well as a group of countries with an average inflation rate of at most 8% (which we call "low inflation countries").

5.2 Estimation Results

Table 1 provides evidence on the integration and cointegration properties of the three variables entering the PPP hypothesis, nominal effective exchange rates, e, domestic prices, p and weighted ("effective") foreign prices, p^*. While for our sample there is strong evidence that p and p^* are I(1) variables, somewhat surprisingly the evidence in favor of nominal exchange rates to be I(1) is less compelling. However, even if e was not I(1), the cointegration tests strongly suggest that there is a long-run relation between exchange rates, domestic prices and foreign prices. Thus, the error-correction specification of the ARDL model in Equation (27) is correct, and we can draw inference on the basis of it.

Table 1: Stationarity Properties for 71 Countries, 1970 to 2004

	a. Panel Unit-Root Test	
	Level	First Difference
e	−2.9805	−3.3113
p	−1.9815	−2.7271
p^*	−2.3187	−3.3014
	b. Panel Cointegration Test	
	VR_P	VR_G
$e + \theta_1(\tilde{z})p + \theta_2(\tilde{z})p^*$	−4.9449	−6.4125

Notes: The panel unit-root test (part a) is computed according to Pesaran (2006b) and has a non-standard distribution under the null hypothesis of a unit root in the time series of all countries. Under the alternative hypothesis, the variable is stationary for a non-vanishing share of countries. Levels of the variables are modelled with a constant and a linear time trend, the specifications for first differences include a constant only. The critical value at the 5% (1%) significance level for the level of a variable is −2.58 (−2.69) and −2.08 (−2.19) for the first difference of a variable. Both panel cointegration test statistics (part b) are distributed standard normal under the null of no cointegration. VR_P refers to the Panel Variance Ratio Statistic in Westerlund (2005), which has the alternative hypothesis that cointegration prevails for all countries, whereas VR_G is the Group Mean Statistic which has the alternative hypothesis that cointegration prevails for a non-vanishing share of countries. The test has been conducted using Chebyshev polynomials of order three for the estimation of conditionally homogeneous long-run coefficients. The lag orders in both parts have been selected according to the Akaike Information Criterion based on a maximum lag length of 2, but the results are robust to other choices, as well as to lag selection on the basis of other criteria such as the Schwartz Bayesian Criterion.

Table 2 reports on the long-run coefficients for domestic and foreign prices in the long-run relation between exchange rates, domestic prices and foreign prices, as well as the speed of adjustment to this long-run relation under different estimation procedures. The first two columns report MG and PMG estimation results, whereas the third and fourth columns show the average estimates across all states obtained under CPMG and SKMG.

Perhaps most remarkable among the various estimates are the high speed of adjustment coefficients 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) argued to be present.

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

	MG	PMG	CPMG	SKMG
α	**−0.4325** (0.0339)	**−0.3110** (0.0244)	**−0.3533** (0.0021)	**−0.3074** (0.0000)
θ_1	0.1715 (0.2238)	**0.5510** (0.0896)	**0.7374** (0.0314)	**0.6304** (0.0285)
θ_2	−1.0882 (0.2131)	**−0.8097** (0.0779)	**−0.8736** (0.0322)	**−0.6897** (0.0310)

Notes: Cross-section averages of the speed of adjustment coefficient α_i and the long-run coefficients on the domestic (θ_1) and foreign (θ_2) price index. PPP theory 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 $\tilde{z}_{it}$. The lag length is selected according to the AIC with maximum lag of 2. Standard errors are presented in parentheses below the coefficients, figures in bold face denote significance at the 5% level.

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. Our graphs pick up on this point, and, taking into account both the CPMG and SKMG estimates, as the main message for our full sample of countries, suggest strong dependence of the long-run coefficients on a country's international investment position. In environments of limited negative NFA to GDP ratios (of about minus one half to minus one) we find strong evidence that foreign exchange markets appear to view the PPP relation as a strong anchor for the pricing of currencies: The long-run coefficients on domestic and foreign prices are economically and partially even statistically insignificantly different from one and minus one, respectively. For other states of the international investment position, however, the long-run relation bears little resemblance with what PPP would suggest.

Concerning the speed of adjustment coefficients, they also display very sizeable variation across different states of the NFA to GDP ratio, at least under our CPMG approach. For the latter, the speed of adjustment coefficient can be as high as implying a half life of just one year for an NFA to GDP ratio of approximately -0.9, and shrink towards (almost) zero for an NFA to GDP position close to zero. Thus, the international investment position matters both for the short-run adjustment dynamics, and the medium- to long-run relation.

Beyond the results for the full sample of 71 countries, our figures also list the corresponding results for three sample splits: (i) industrial and emerging market economies vs. developing countries, (ii) relatively fixed exchange rates (towards the relevant anchor currency, typically the U.S. Dollar) vs. relatively flexible exchange rates, and (iii) countries with a relatively strong record of price stability vs. countries with relatively limited price stability.

The various graphs suggest that the dependence of the long-run relation between exchange rates, domestic prices and foreign prices on the international investment position that we found for the full sample of countries is more pronounced for developing countries, under fixed exchange rates and in environments of relatively limited price stability than otherwise. However, the significant role of the international investment position for the nature of the long-run relation – namely, whether it corresponds to PPP – and the speed of adjustment towards it is maintained across all environments.

Finally, the last sets of figures shed some light on the potential implications of our estimates for the future medium- to long-run development of five currencies: the U.S. Dollar, the British Pound Sterling, the Japanese Yen, the Turkish Lira, and the Deutsche Mark as a proxy for the Euro. We extrapolated the NFA to GDP ratio, as well as domestic and foreign price indices and the common factors, for each country to keep rising/falling at the average in-sample rate. Subsequently, we computed the implied long-run relation and adjustment coefficients from the CPMG model to obtain implied parity values of the five currencies according to the following relation:

$$\hat{e}_i = \hat{\theta}_1(\tilde{z}_{i,t})\hat{p}_{i,t} + \hat{\theta}_2(\tilde{z}_{i,t})\hat{p}^*_{i,t} - \frac{\hat{\eta}_i \bar{e}_t + \hat{\zeta}_i(\bar{p}_t - \bar{p}^*_t) + \hat{\mu}_i}{\hat{\alpha}_i(\tilde{z}_{i,t})}, \quad t = T+1, T+2, \ldots, T^*, \qquad (28)$$

where T^* denotes the end of the projection period, in our case the year 2025. Our results predict a further real effective depreciation of approximately 27% of the U.S. Dollar over the next twenty years (see Table E.1) simply due to changes in the NFA to GDP ratio. A similar order of magnitude of real depreciation can be observed for the Yen and the Turkish Lira. Based on this exercise, the effects on the Deutsche Mark and the Pound Sterling are comparably small. On a bilateral basis, the results from projections based on extrapolations of the NFA to GDP ratio are rather mixed (see Table E.2). After twenty years, the U.S. Dollar loses around 22% of its value against the Pound Sterling and almost as much against the Deutsche Mark, but appreciates by around 6% against the Yen and around 12% against the Turkish Lira. The Deutsche Mark in turn appreciates against the other currencies but is largely unchanged in value against the Pound Sterling.

6 Conclusion

In this paper we revisited medium- to long-run exchange rate determination, focussing on international flows of capital. To do so, we developed a new econometric framework accounting for conditional homogeneity in heterogeneous dynamic panel data models. In particular, in our model the long-run relationship between exchange rates and domestic as well as international prices has been specified as a function of a country's international investment position. We found rather strong support for purchasing power parity in environments of limited negative net foreign asset to GDP positions, but not outside such environments. We thus argued that the purchasing power parity hypothesis holds conditionally, but not unconditionally, and that international flows of capital and the cumulative stock positions they imply are key to characterizing this conditionality.

Our future research will address in particular two issues: (i) the extension of CPMG and SKMG models to multivariate conditioning keeping model parameterizations in parsimony, and (ii) the extension of at least part of our database to bilateral measurement of international capital flows, allowing to analyze in depth the implications of such flows and their effects on stocks of international investment positions as macroeconomic and financial aggregates.

Appendix

A Valuation Adjustment

We are following the principles for valuation adjustment as described in Appendix A of Lane and Milesi-Ferretti (2001). FDI assets are adjusted for changes in the real (trade-weighted) dollar exchange rate of country i's trade partners:

$$\Delta FDIA_{it} = DFDIA_{i,t-1} + \Delta V(FDIA)_{it} \tag{A.1}$$

where $DFDIA_{it}$ is the flow of FDI assets from country i in period t. $\Delta V(FDIA)_{it}$ is the change in the value of the FDI asset stock from the end of period $t-1$ to the end of period t, with

$$\Delta V(FDIA)_{it} = \left(\frac{\tilde{q}_{it}}{\tilde{q}_{i,t-1}} - 1\right) FDIA_{i,t-1}, \tag{A.2}$$

$$\tilde{q}_{it} = \exp\left\{\sum_{j=1}^{N} \ln\left(\frac{CPI_{jt}}{CPI_{US,t}} \cdot s_{j,t}\right) \cdot w_{ijt}\right\}, \tag{A.3}$$

CPI denoting the consumer price index and $s_{j,t}$ country j's exchange rate in U.S. dollar per unit of domestic currency. The weight w_{ijt} is calculated as country i's trade (that is, the sum of exports, EXP, and imports, IMP) with country j relative to country i's total trade for each year, namely

$$w_{ijt} = \frac{|EXP_{ijt}| + |IMP_{ijt}|}{\sum_{j=1}^{N} |EXP_{ijt}| + |IMP_{ijt}|}. \tag{A.4}$$

FDI liabilities are adjusted using analogous formulae, namely:

$$\Delta FDIL_{it} = DFDIL_{i,t-1} + \Delta V(FDIL)_{it} \tag{A.5}$$

where $DFDIL_{it}$ denotes the flow of FDI liabilities to country i in period t, and the change in the stock value is defined as

$$\Delta V(FDIL)_{it} = \left(\frac{q_{it}}{q_{i,t-1}} - 1\right) FDIL_{i,t-1}, \tag{A.6}$$

with

$$q_{it} = \frac{CPI_{it}}{CPI_{US,t}} \cdot s_{it}. \tag{A.7}$$

Equity assets (domestic holdings of foreign equity shares) are adjusted by changes in the MSCI World Index, m, assuming that equity investment abroad is allocated according to the world portfolio that is approximated by this index.[10] Decomposing the change in the stock into

$$\Delta EQA_{it} = DEQA_{i,t-1} + \Delta V(EQA)_{it}, \tag{A.8}$$

where $DEQA_{it}$ refers to the flow of equity assets from country i in period t, we compute the change in the value of the stock as

$$\Delta V(EQA)_{it} = \left(\frac{m_t}{m_{t-1}} - 1\right) EQA_{i,t-1} + \left(\frac{m_t}{\sqrt{m_t m_{t-1}}} - 1\right) DEQA_{it}, \tag{A.9}$$

taking into account that m_t refers to end-of-period values, whereas flows are assumed to occur throughout the year and thus, at an average value of $\sqrt{m_t m_{t-1}}$.

Equity liabilities (foreign holdings of domestic equity shares) are adjusted by changes in domestic (or regional) stock market indices m_i in the same vein as equity assets, with

$$\Delta EQL_{it} = DEQL_{i,t-1} + \Delta V(EQL)_{it}, \tag{A.10}$$

$DEQL_{it}$ denoting the flow of equity liabilities to country i in period t, and

$$\Delta V(EQL)_{it} = \left(\frac{m_{it}}{m_{i,t-1}} - 1\right) EQL_{i,t-1} + \left(\frac{m_{it}}{\sqrt{m_{it} m_{i,t-1}}} - 1\right) DEQL_{it}. \tag{A.11}$$

Finally, we infer changes to the stock of international reserves excluding gold holdings (RES^*) from the difference between the change in official reserves (RES) according to IIP and recorded reserve flows ($DRES$):

$$\Delta V(RES^*)_{it} = \Delta RES_{it} - DRES_{it}. \tag{A.12}$$

Consequently, the net valuation change used for adjusting the cumulative flow measure for NFA is constructed as

$$\Delta NV_{it} = \Delta V(FDIA)_{it} - \Delta V(FDIL)_{it} + \Delta V(EQA)_{it} - \Delta V(EQL)_{it} + \Delta V(RES^*)_{it}. \tag{A.13}$$

[10] Note that for the U.S., Japan and the UK we use an adjusted index that in each case excludes these countries from the definition of the rest of the world.

B Two-Step Estimation of the CPMG Model

Let the linear form of the model for an individual observation be

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

where $\boldsymbol{\psi}_i(\tilde{z}_{it})$ is the (state-dependent) coefficient vector of the variables not relevant for the long-run relationship and the speed of adjustment that are summarized in $\boldsymbol{h}_{it}$.

Then, the model can be written in stacked form by diagonalizing the vectors of time-varying coefficients. To that aim, write (B.1) for each cross-section unit as

$$\Delta \boldsymbol{y}_i = \boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{y}_{i,-1} + \boldsymbol{B}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_i + \boldsymbol{\Psi}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{h}}_i + \boldsymbol{\varepsilon}_i \tag{B.2}$$

$$= \boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)[\boldsymbol{y}_{i,-1} + \boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)^{-1}\boldsymbol{B}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_i] + \boldsymbol{\Psi}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{h}}_i + \boldsymbol{\varepsilon}_i \tag{B.3}$$

$$= \boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)[\boldsymbol{y}_{i,-1} - \boldsymbol{\Theta}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_i] + \boldsymbol{\Psi}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{h}}_i + \boldsymbol{\varepsilon}_i, \tag{B.4}$$

where $\tilde{\boldsymbol{x}}_i = [\boldsymbol{x}'_{1,i}\ \boldsymbol{x}'_{2,i}\ \ldots\ \boldsymbol{x}'_{k,i}]'$, $\tilde{\boldsymbol{h}}_i = [\boldsymbol{h}'_{1,i}\ \boldsymbol{h}'_{2,i}\ \ldots\ \boldsymbol{h}'_{m,i}]'$, $m = 2p+1+2k(q+1)$, and the time-dependent coefficients are specified as (block-) diagonal matrices with

$$\boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i) = \text{diag}[\alpha_i(\tilde{z}_{i1}), \alpha_i(\tilde{z}_{i2}), \ldots, \alpha_i(\tilde{z}_{iT})],$$

$$\boldsymbol{B}_i(\tilde{\boldsymbol{z}}_i) = [\boldsymbol{B}_{1,i}(\tilde{\boldsymbol{z}}_i)\ \ \boldsymbol{B}_{2,i}(\tilde{\boldsymbol{z}}_i)\ \ \ldots\ \ \boldsymbol{B}_{k,i}(\tilde{\boldsymbol{z}}_i)],$$

$$\boldsymbol{B}_{l,i}(\tilde{\boldsymbol{z}}_i) = \text{diag}[\beta_{l,i}(\tilde{z}_{i1}), \beta_{l,i}(\tilde{z}_{i2}), \ldots, \beta_{l,i}(\tilde{z}_{iT})], \quad l = 1, 2, \ldots, k,$$

$$\boldsymbol{\Psi}_i(\tilde{\boldsymbol{z}}_i) = [\boldsymbol{\Psi}_{1,i}(\tilde{\boldsymbol{z}}_i)\ \ \boldsymbol{\Psi}_{2,i}(\tilde{\boldsymbol{z}}_i)\ \ \ldots\ \ \boldsymbol{\Psi}_{m,i}(\tilde{\boldsymbol{z}}_i)],$$

$$\boldsymbol{\Psi}_{r,i}(\tilde{\boldsymbol{z}}_i) = \text{diag}[\psi_{r,i}(\tilde{z}_{i1}), \psi_{r,i}(\tilde{z}_{i2}), \ldots, \psi_{r,i}(\tilde{z}_{iT})], \quad r = 1, 2, \ldots, m,$$

and

$$\boldsymbol{\Theta}_i(\tilde{\boldsymbol{z}}_i) \equiv -\boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)^{-1}\boldsymbol{B}_i(\tilde{\boldsymbol{z}}_i).$$

Note that

$$\boldsymbol{\Theta}_i(\tilde{\boldsymbol{z}}_i) = [\boldsymbol{\Theta}_{1,i}(\tilde{\boldsymbol{z}}_i)\ \ \boldsymbol{\Theta}_{2,i}(\tilde{\boldsymbol{z}}_i)\ \ \ldots\ \ \boldsymbol{\Theta}_{k,i}(\tilde{\boldsymbol{z}}_i)],$$

$$\boldsymbol{\Theta}_{l,i}(\tilde{\boldsymbol{z}}_i) = \text{diag}[\theta_{l,i}(\tilde{z}_{i1}), \theta_{l,i}(\tilde{z}_{i2}), \ldots, \theta_{l,i}(\tilde{z}_{iT})], \quad l = 1, 2, \ldots, k,$$

satisfying

$$\theta_{l,i}(\tilde{z}_{it}) = -\alpha_i(\tilde{z}_{it})^{-1}\beta_{l,i}(\tilde{z}_{it}).$$

Now, to represent the time-varying coefficients as polynomials in the conditioning variable $\tilde{z}_{it}$, define the matrix of polynomial elements up to order τ as

$$\boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i) \equiv [c_0(\tilde{\boldsymbol{z}}_i) \;\; c_1(\tilde{\boldsymbol{z}}_i) \;\; \dots \;\; c_\tau(\tilde{\boldsymbol{z}}_i)] \tag{B.5}$$

with dimension $T \times (\tau + 1)$, given that the vector elements are constructed as

$$c_s(\tilde{\boldsymbol{z}}_i) = [c_s(\tilde{z}_{i1}) \;\; c_s(\tilde{z}_{i2}) \;\; \dots c_s(\tilde{z}_{iT})]', \quad s = 0, 1, \dots, \tau.$$

The key model coefficients are then specified as follows:

$$\begin{aligned} \boldsymbol{\alpha}_i(\tilde{\boldsymbol{z}}_i) &= \boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\alpha)} \\ \boldsymbol{\gamma}_i^{\alpha} &= \left[\gamma_{i,0}^{(\alpha)} \;\; \gamma_{i,1}^{(\alpha)} \;\; \dots \;\; \gamma_{i,\tau}^{(\alpha)}\right]', \end{aligned} \tag{B.6}$$

$$\begin{aligned} \boldsymbol{\beta}_{l,i}(\tilde{\boldsymbol{z}}_i) &= \boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta_l)} \\ \boldsymbol{\gamma}_i^{(\beta_l)} &= \left[\gamma_{i,0}^{(\beta_l)} \;\; \gamma_{i,1}^{(\beta_l)} \;\; \dots \;\; \gamma_{i,\tau}^{(\beta_l)}\right]' \end{aligned} \tag{B.7}$$

$$\begin{aligned} \boldsymbol{\psi}_{r,i}(\tilde{\boldsymbol{z}}_i) &= \boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\psi_r)} \\ \boldsymbol{\gamma}_i^{(\psi_r)} &= \left[\gamma_{i,0}^{(\psi_r)} \;\; \gamma_{i,1}^{(\psi_r)} \;\; \dots \;\; \gamma_{i,\tau}^{(\psi_r)}\right]' \end{aligned} \tag{B.8}$$

$$\begin{aligned} \boldsymbol{\theta}_{l,i}(\tilde{\boldsymbol{z}}_i) &= \boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\theta_l)} \\ \boldsymbol{\gamma}_i^{(\theta_l)} &= \left[\gamma_{i,0}^{(\theta_l)} \;\; \gamma_{i,1}^{(\theta_l)} \;\; \dots \;\; \gamma_{i,\tau}^{(\theta_l)}\right]'. \end{aligned} \tag{B.9}$$

Inserting the polynomial specification for the time-varying coefficients, we obtain

$$\begin{aligned} \boldsymbol{B}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_i &= \sum_{l=1}^{k} \boldsymbol{B}_{l,i}(\tilde{\boldsymbol{z}}_i)\boldsymbol{x}_{l,i} \\ &= \sum_{l=1}^{k} \text{diag}[\boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta_l)}]\boldsymbol{x}_{l,i} \\ &= \sum_{l=1}^{k} \text{diag}(\boldsymbol{x}_{l,i})\boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta_l)} \\ &= \boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta)}, \end{aligned} \tag{B.10}$$

where

$$\boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i) = [\boldsymbol{\mathcal{X}}_{1,i}(\tilde{\boldsymbol{z}}_i) \;\; \boldsymbol{\mathcal{X}}_{2,i}(\tilde{\boldsymbol{z}}_i) \;\; \ldots \;\; \boldsymbol{\mathcal{X}}_{k,i}(\tilde{\boldsymbol{z}}_i)],$$

$$\boldsymbol{\mathcal{X}}_{l,i}(\tilde{\boldsymbol{z}}_i) = \mathrm{diag}(\boldsymbol{x}_{l,i})\boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i), \quad l = 1, 2, \ldots, k, \text{ and}$$

$$\boldsymbol{\gamma}_i^{(\beta)} = \left[\boldsymbol{\gamma}_i^{(\beta_1)\prime} \;\; \boldsymbol{\gamma}_i^{(\beta_2)\prime} \;\; \ldots \;\; \boldsymbol{\gamma}_i^{(\beta_k)\prime}\right]'.$$

In analogous fashion, it holds that

$$\boldsymbol{A}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{y}_{i,-1} = \boldsymbol{\mathcal{Y}}_{i,-1}(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\alpha)}, \tag{B.11}$$

with

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

and

$$\boldsymbol{\Psi}_i(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{h}}_i = \boldsymbol{\mathcal{H}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta)}, \tag{B.12}$$

with

$$\boldsymbol{\mathcal{H}}_i(\tilde{\boldsymbol{z}}_i) = [\boldsymbol{\mathcal{H}}_{1,i}(\tilde{\boldsymbol{z}}_i) \;\; \boldsymbol{\mathcal{H}}_{2,i}(\tilde{\boldsymbol{z}}_i) \;\; \ldots \;\; \boldsymbol{\mathcal{H}}_{m,i}(\tilde{\boldsymbol{z}}_i)],$$

$$\boldsymbol{\mathcal{H}}_{r,i}(\tilde{\boldsymbol{z}}_i) = \mathrm{diag}(\boldsymbol{h}_{r,i})\boldsymbol{\Pi}_\tau(\tilde{\boldsymbol{z}}_i), \quad r = 1, 2, \ldots, m,$$

$$\boldsymbol{\gamma}_i^{(\psi)} = \left[\boldsymbol{\gamma}_i^{(\psi_1)\prime} \;\; \boldsymbol{\gamma}_i^{(\psi_2)\prime} \;\; \ldots \;\; \boldsymbol{\gamma}_i^{(\psi_m)\prime}\right]'$$

such that (B.2) becomes

$$\Delta\boldsymbol{y}_i = \boldsymbol{\mathcal{Y}}_{i,-1}(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\alpha)} + \boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\beta)} + \boldsymbol{\mathcal{H}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}_i^{(\psi)} + \boldsymbol{\varepsilon}_i. \tag{B.13}$$

Once the adjustment coefficients and the other parameters have been estimated from (B.13), we can insert them in the second step to obtain the coefficients of the long-run relationship by pooled least-squares estimation of

$$\boldsymbol{v}_i = -\boldsymbol{\Theta}(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_i + \boldsymbol{\nu}_i, \tag{B.14}$$

where

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

$$\boldsymbol{\nu}_i = \hat{\boldsymbol{A}}_i(\tilde{\boldsymbol{z}}_i)^{-1}\boldsymbol{\varepsilon}_i,$$

and

$$V(\boldsymbol{\nu}_i) = \hat{\boldsymbol{A}}_i(\tilde{\boldsymbol{z}}_i)^{-2}\hat{\sigma}_i^2.$$

Again, inserting the polynomial specification for the long-run coefficients, we have

$$\boldsymbol{\Theta}(\tilde{\boldsymbol{z}}_i)\tilde{\boldsymbol{x}}_{i,-1} = \boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}^{(\theta)}, \tag{B.15}$$

with

$$\boldsymbol{\gamma}^{(\theta)} = \left[\boldsymbol{\gamma}^{(\theta_1)\prime} \ \ \boldsymbol{\gamma}^{(\theta_2)\prime} \ \ \dots \ \ \boldsymbol{\gamma}^{(\theta_k)\prime}\right]',$$

such that (B.14) becomes

$$\boldsymbol{v}_i = -\boldsymbol{\mathcal{X}}_i(\tilde{\boldsymbol{z}}_i)\boldsymbol{\gamma}^{(\theta)} + \boldsymbol{\nu}_i. \tag{B.16}$$

C Computation of Standard Errors for Speed of Adjustment Coefficients

Under the CPMG approach, we have estimated N heterogeneous functional forms for the speed of adjustment coefficient α, such that

$$\hat{\alpha}_{j,it} = \hat{\alpha}_j(\tilde{z}_{it}), \ i = 1, 2, ..., N, \ t = 1, 2, ..., T \ j = 1, 2, ..., N \tag{C.1}$$

is the estimate of α 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 for the mean relationship in the panel by averaging across country-specific estimates, with

$$\hat{\alpha}_{it}^{MG} = \bar{\alpha}(\tilde{z}_{it}). \tag{C.2}$$

The heterogeneous functional forms are based on Chebyshev polynomials up to order τ, with polynomial terms $c_s(\tilde{z}_{it})$ and parameters $\gamma_{js}^{(\alpha)}$, $s = 0, 1, ..., \tau$. The mean coefficient at the point $\tilde{z}_{it}$ should therefore be an average of the coefficients implied by each polynomial. However, the polynomial function for α_j is estimated on the basis of the observations for country j only and therefore might be valid only in a limited range of values for $\tilde{z}_{it}$. 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 $\hat{\alpha}_j(\tilde{z}_{it})$, where the weights decrease with the distance of $\tilde{z}_{it}$ from the mean for country j, $\bar{z}_j$. The distance may be incorporated using a kernel specification similar to the state kernel mean group (SKMG) approach:

In particular, let $\hat{\boldsymbol{\gamma}}_j^{(\alpha)}$ be the $\tau + 1$ vector of estimated polynomial coefficients for country j and $\hat{\boldsymbol{\Sigma}}_{\gamma,j}$ its covariance matrix. Then,

$$\hat{\alpha}_{j,it} = \hat{\boldsymbol{\gamma}}_j^{(\alpha)\prime}\boldsymbol{\pi}_\tau(\tilde{z}_{it}), \tag{C.3}$$

where $\boldsymbol{\pi}_\tau(\tilde{z}_{it}) = [c_0(\tilde{z}_{it}), c_1(\tilde{z}_{it}), \ldots, c_\tau(\tilde{z}_{it})]'$. The variance of $\hat{\alpha}_{j,it}$ can be computed from

$$\hat{\sigma}^2_{\alpha,j,it} = \boldsymbol{\pi}_\tau(\tilde{z}_{it})'\hat{\boldsymbol{\Sigma}}_{\gamma,j}\boldsymbol{\pi}_\tau(\tilde{z}_{it}). \tag{C.4}$$

The weights are obtained from the kernel specification

$$k_{j,it} = \mathcal{K}(\frac{\tilde{z}_{it} - \bar{z}_j}{h}),$$

where $\mathcal{K}(\cdot)$ is the Gaussian kernel and h is the bandwidth, computed in the standard way as $h = 1.06\,\sigma_{\tilde{z}}(NT)^{-1/5}$, with $\sigma_{\tilde{z}}$ representing the overall standard deviation of $\tilde{z}_{it}$.

We have to standardize the weights to ensure a proper definition of the weighted average, constructing

$$w_{j,it} = \frac{k_{j,it}}{\sum_{j=1}^N k_{j,it}}. \tag{C.5}$$

Now we are in a position to construct a smoothed mean group estimator of α from

$$\hat{\alpha}^{SMG}_{it} = \sum_{j=1}^N \hat{\alpha}_{j,it} w_{j,it}, \tag{C.6}$$

and the corresponding standard error from

$$\hat{\sigma}^{SMG}_{\alpha,it} = \sqrt{\frac{1}{N-1}\sum_{j=1}^N \left(\hat{\alpha}_{j,it} - \hat{\alpha}^{SMG}_{it}\right)^2 w_{j,it}}. \tag{C.7}$$

D Kernel Specification

Define $k(\tilde{z}_{it} - \tilde{z}_{js}) \equiv \mathcal{K}\left(\frac{\tilde{z}_{it}-\tilde{z}_{js}}{h}\right)$, where $\mathcal{K}(\cdot)$ is a standard kernel function such as the Epanechnikov or Gaussian kernel.

Then, for a given combination of cross-sectional reference point j and time-series reference point s the kernel matrix for group i looks as follows:

$$\begin{aligned}\boldsymbol{K}_i(\tilde{z}_{js}) &= \begin{pmatrix} k(\tilde{z}_{i1} - \tilde{z}_{j,s}) & & & & 0 \\ & \ddots & & & \\ & & k(\tilde{z}_{it} - \tilde{z}_{js}) & & \\ & & & \ddots & \\ 0 & & & & k(\tilde{z}_{iT} - \tilde{z}_{js}) \end{pmatrix}_{T\times T} \\ &= k_i(\tilde{z}_{js})\boldsymbol{I}_T, \qquad \text{if } \tilde{z}_{it} \equiv \tilde{z}_i \ \forall\, t. \end{aligned} \tag{D.1}$$

Therefore, the full kernel matrix is

$$\boldsymbol{K}(\tilde{z}_{js}) = \begin{pmatrix} \boldsymbol{K}_1(\tilde{z}_{js}) & & & & \mathbf{0} \\ & \ddots & & & \\ & & \boldsymbol{K}_i(\tilde{z}_{js}) & & \\ & & & \ddots & \\ \mathbf{0} & & & & \boldsymbol{K}_N(\tilde{z}_{js}) \end{pmatrix}_{NT\times NT}$$
$$= \operatorname{diag}[k_1(\tilde{z}_{js}), \ldots, k_i(\tilde{z}_{js}), \ldots, k_N(\tilde{z}_{js})] \otimes \boldsymbol{I}_T, \qquad \text{if } \tilde{z}_{it} \equiv \tilde{z}_i \; \forall \, t. \tag{D.2}$$

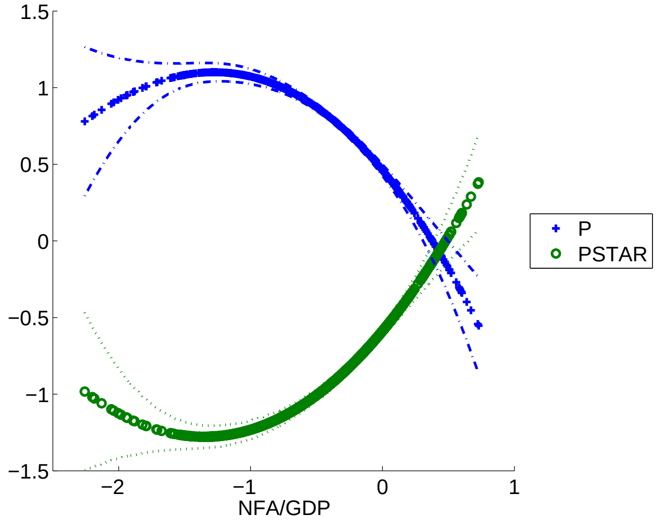
It is apparent that empirical results will be affected by the choice of both the kernel density function $\mathcal{K}$ and the bandwidth parameter h. Nevertheless, the specific kernel function is not crucial to the outcome since for kernels belonging to the same class, the bandwidth parameter can be adjusted using "canonical kernels" such that the estimated functions are largely equivalent. Referring to the Gaussian kernel, we follow Pagan and Ullah (1999, p. 26) and choose the bandwidth parameter as

$$h = 1.06\,\sigma_{\tilde{z}}(NT)^{-1/5}, \tag{D.3}$$

where $\sigma_{\tilde{z}}$ is the standard deviation of the conditioning variable $\tilde{z}_{it}$ across time and cross sections.

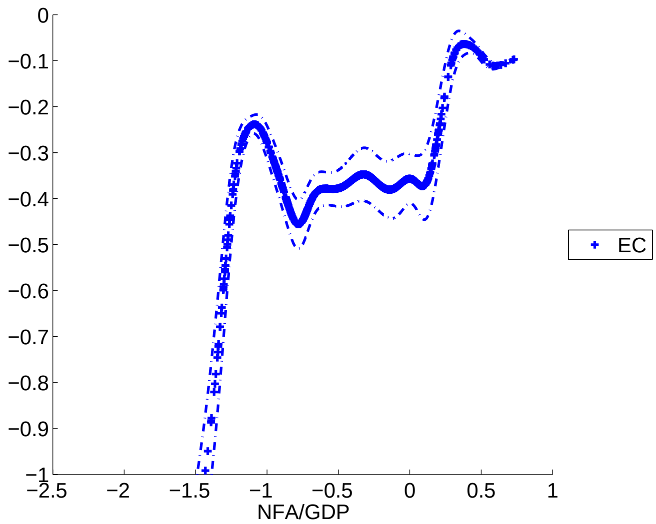
E Figures & Tables

Figure E.1: Long-Run Coefficients for 71 Countries, 1970–2004:
CPMG Approach



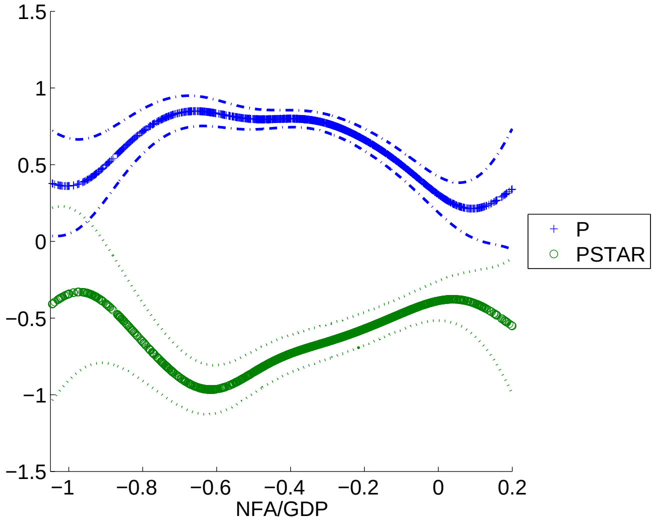
Notes: Homogeneous estimates of the long-run coefficients between exchange rates and prices in Equation (27) using Chebyshev polynomials of order three in the conditioning variable, a 10-year moving average of the NFA to GDP ratio. The lag length is selected according to the AIC with maximum lag of 2. Standard error bands denote the 95% confidence interval of the estimates.

Figure E.2: Adjustment Coefficients for 71 Countries, 1970–2004:
CPMG Approach



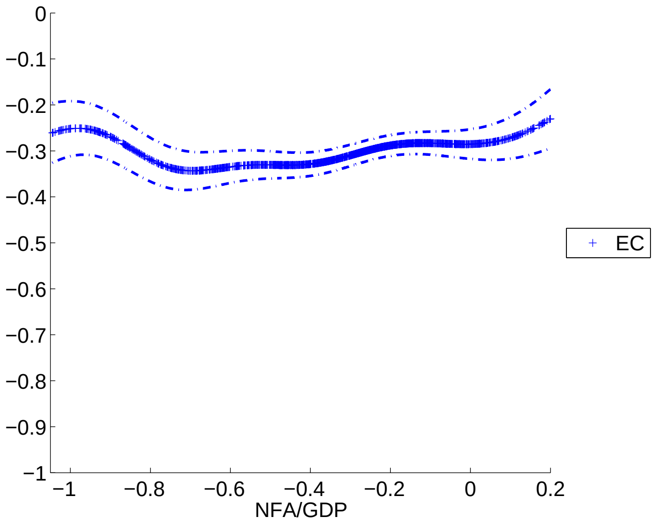
Notes: Smoothed mean group estimates of heterogeneous adjustment coefficients in Equation (27) using Chebyshev polynomials of order one in the conditioning variable, a 10-year moving average of the NFA to GDP ratio. The lag length is selected according to the AIC with maximum lag of 2. Standard error bands denote the 95% confidence interval of the estimates.

Figure E.3: Long-Run Coefficients for 71 Countries, 1970–2004:
SKMG Approach



Notes: Estimates of the long-run coefficients between exchange rates and prices in Equation (27) using local kernels in the conditioning variable, a 10-year moving average of the NFA to GDP ratio. The lag length is selected according to the AIC with maximum lag of 2. Standard error bands denote the 95% confidence interval of the estimates.

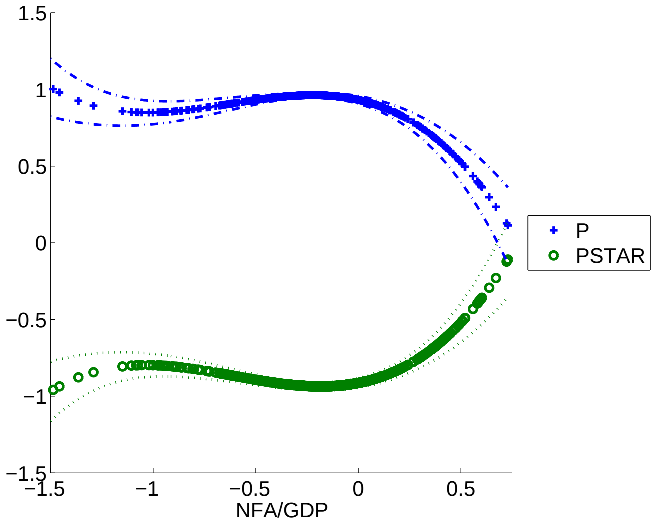
Figure E.4: Adjustment Coefficients for 71 Countries, 1970–2004:
SKMG Approach



Notes: Estimates of the adjustment coefficient in Equation (27) using local kernels in the conditioning variable, a 10-year moving average of the NFA to GDP ratio. The lag length is selected according to the AIC with maximum lag of 2. Standard error bands denote the 95% confidence interval of the estimates.

Figure E.5: Long-Run Coefficients for 32 Industrial & Emerging Market Economies, 1970–2004:

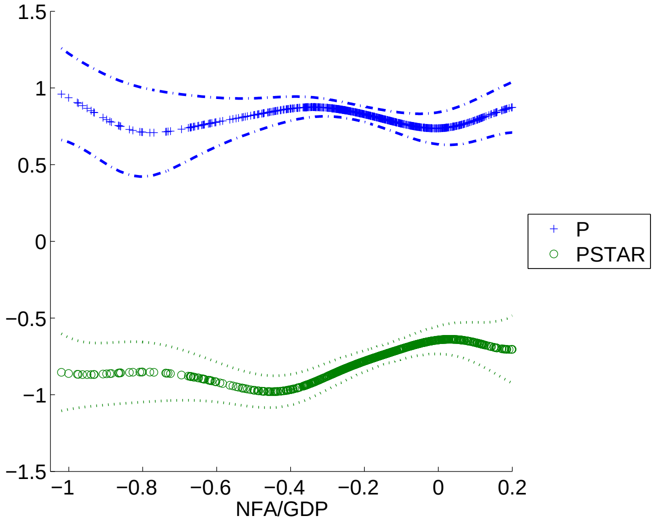
CPMG Approach



Notes: See above.

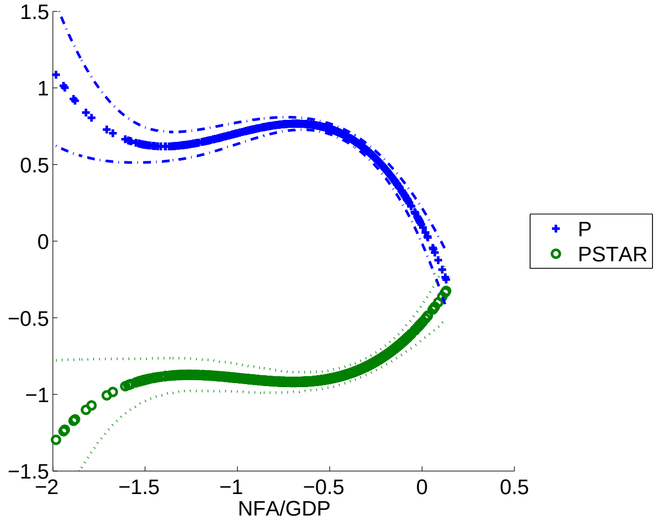
Figure E.6: Long-Run Coefficients for 32 Industrial & Emerging Market Economies, 1970–2004:

SKMG Approach



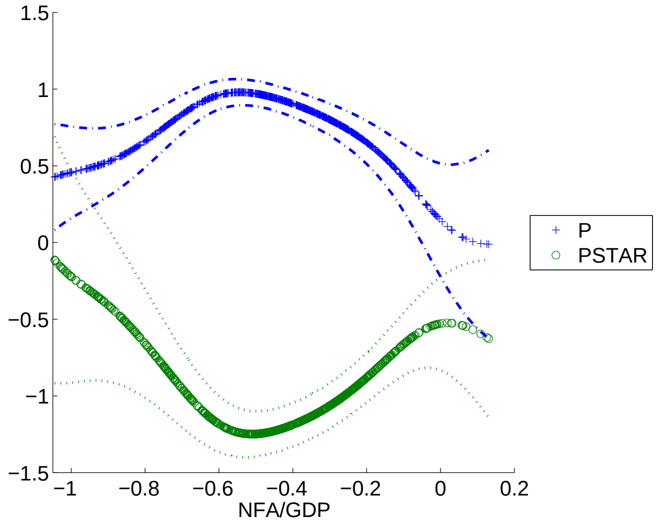
Notes: See above.

Figure E.7: Long-Run Coefficients for 39 Developing Countries, 1970–2004: CPMG Approach



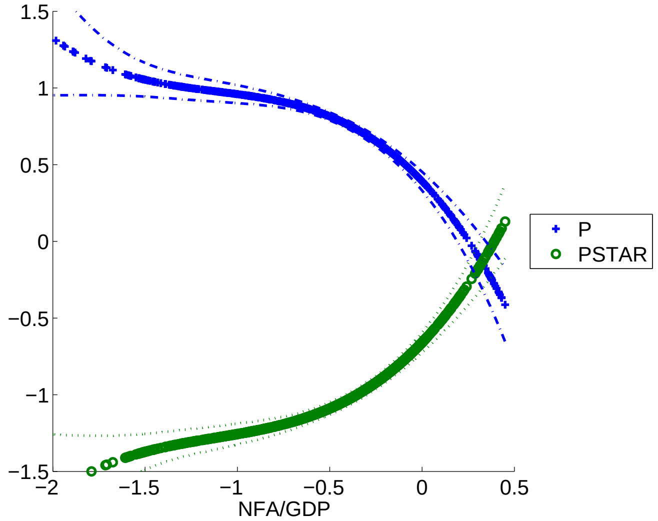
Notes: See above.

Figure E.8: Long-Run Coefficients for 39 Developing Countries, 1970–2004: SKMG Approach



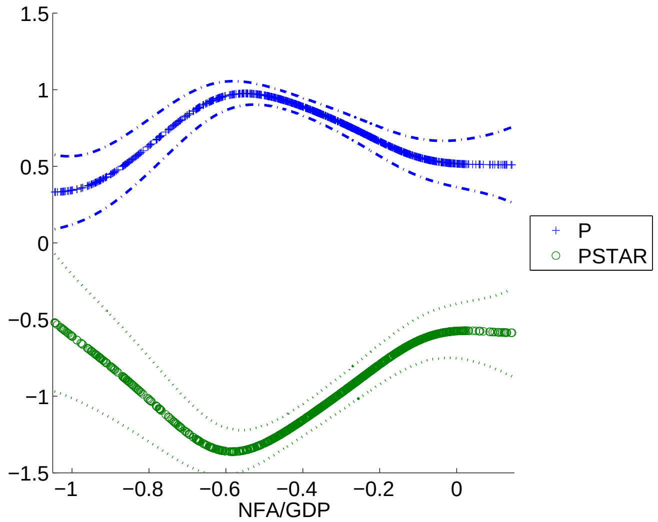
Notes: See above.

Figure E.9: Long-Run Coefficients for 50 Fixed Exchange Rate Currencies, 1970–2004: CPMG Approach



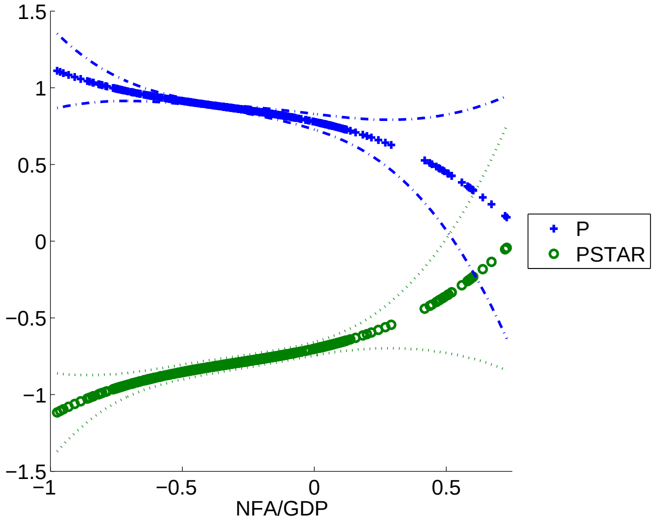
Notes: See above. A country is determined to have a fixed exchange rate if its exchange rate classification code according to the recoded Levy-Yeyati and Sturzenegger (2005) data is larger than 3 on average over the sample period.

Figure E.10: Long-Run Coefficients for 50 Fixed Exchange Rate Currencies, 1970–2004: SKMG Approach



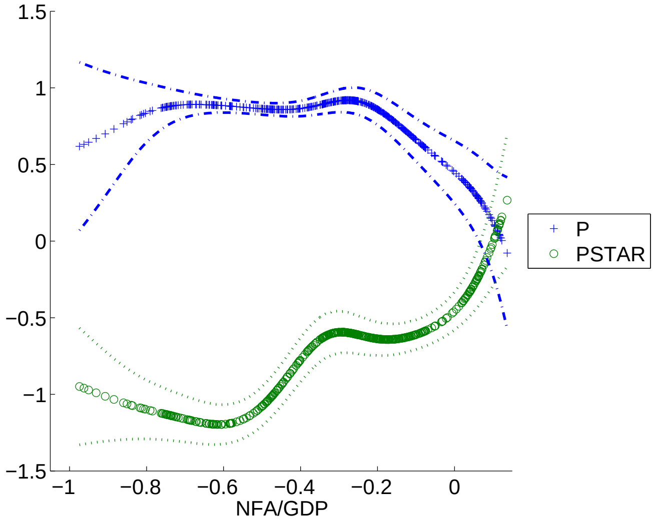
Notes: See above. A country is determined to have a fixed exchange rate if its exchange rate classification code according to the recoded Levy-Yeyati and Sturzenegger (2005) data is larger than 3 on average over the sample period.

Figure E.11: Long-Run Coefficients for 21 Flexible Exchange Rate Countries, 1970–2004: CPMG Approach



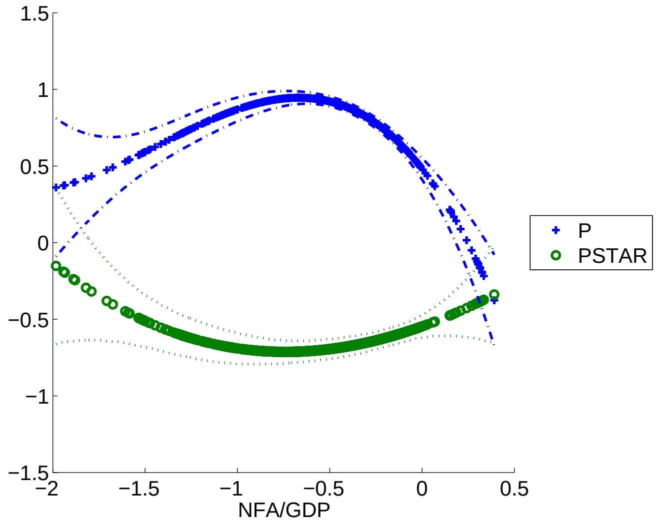
Notes: See above. A country is determined to have a flexible exchange rate if its exchange rate classification code according to the recoded Levy-Yeyati and Sturzenegger (2005) data is not larger than 3 on average over the sample period.

Figure E.12: Long-Run Coefficients for 21 Flexible Exchange Rate Countries, 1970–2004: SKMG Approach



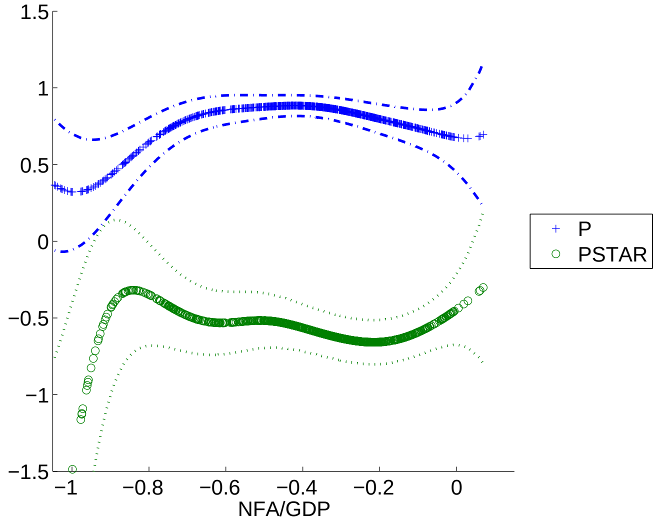
Notes: See above. A country is determined to have a flexible exchange rate if its exchange rate classification code according to the recoded Levy-Yeyati and Sturzenegger (2005) data is not larger than 3 on average over the sample period.

Figure E.13: Long-Run Coefficients for 39 High Inflation Countries, 1970–2004: CPMG Approach



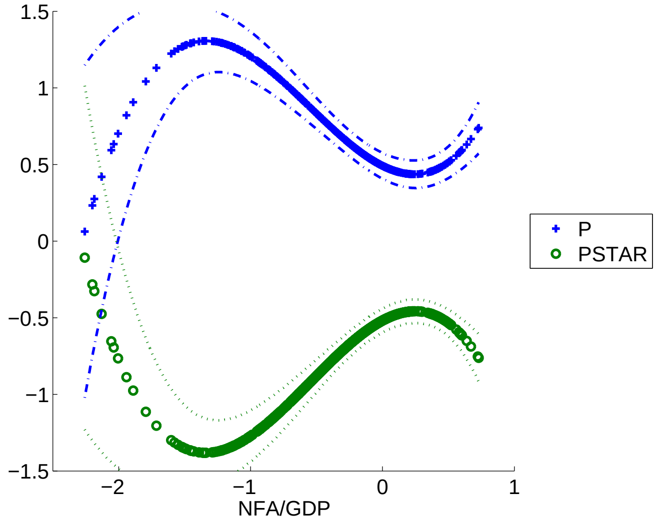
Notes: See above. A country is determined to have a high inflation rate if the annual change in its consumer price index is larger than 8% on average over the sample period.

Figure E.14: Long-Run Coefficients for 39 High Inflation Countries, 1970–2004: SKMG Approach



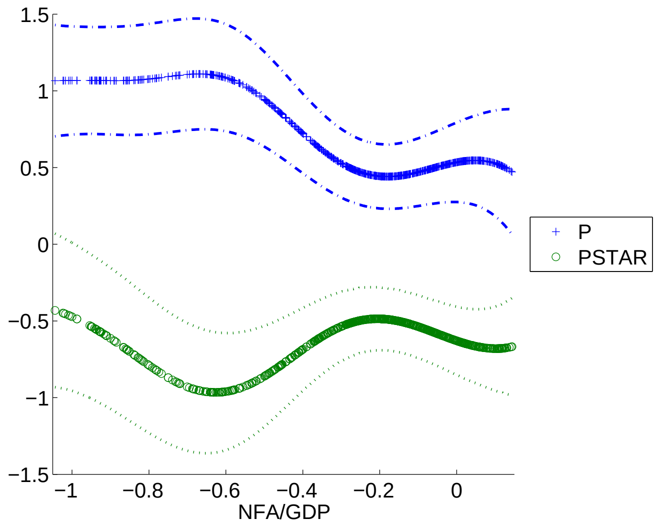
Notes: See above. A country is defined to have a high inflation rate if the annual change in its consumer price index is larger than 8% on average over the sample period.

Figure E.15: Long-Run Coefficients for 32 Low Inflation Countries, 1970–2004: CPMG Approach



Notes: See above. A country is defined to have a low inflation rate if the annual change in its consumer price index is not larger than 8% on average over the sample period.

Figure E.16: Long-Run Coefficients for 32 Low Inflation Countries, 1970–2004: SKMG Approach



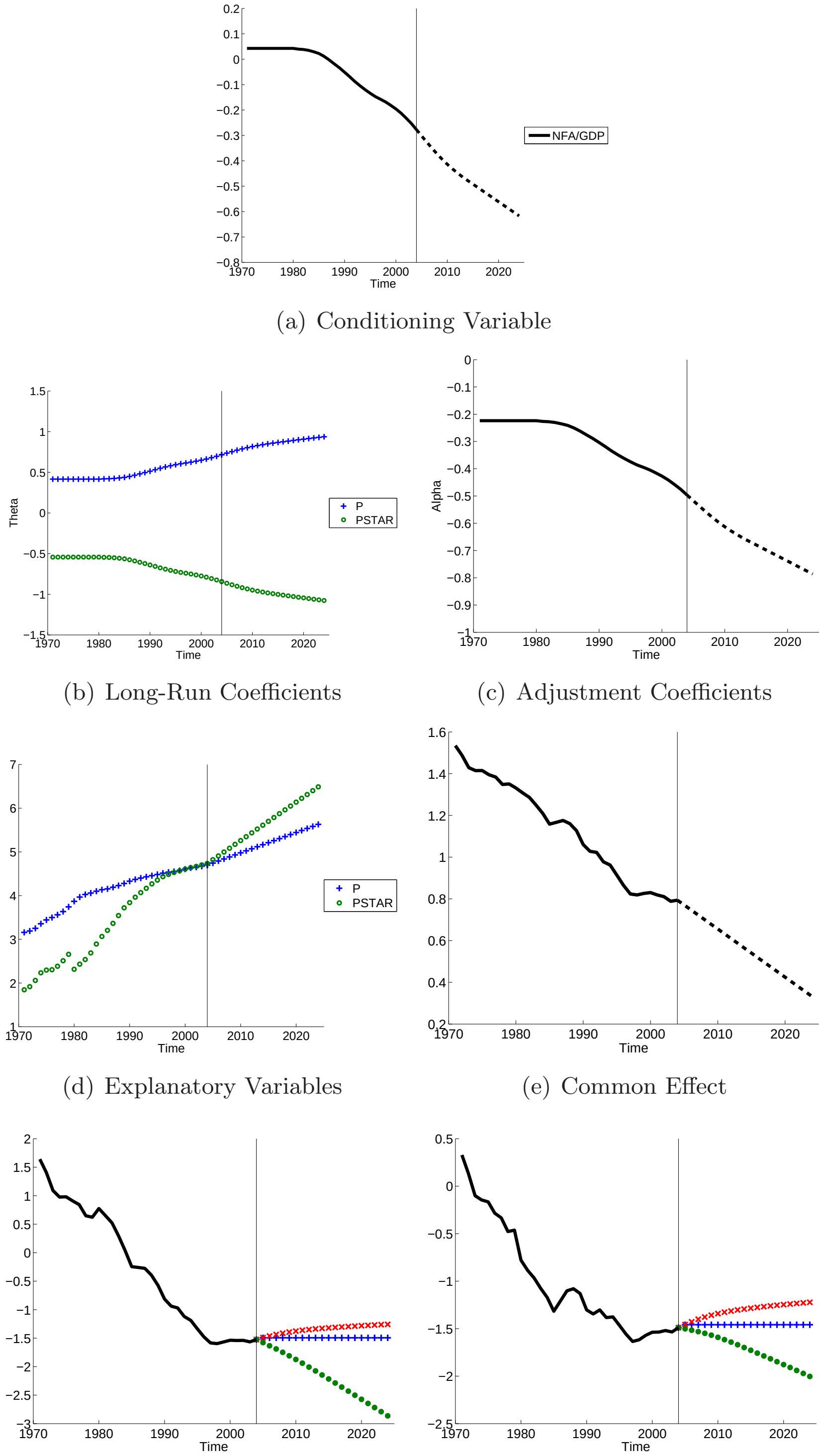
Notes: See above. A country is defined to have a low inflation rate if the annual change in its consumer price index is not larger than 8% on average over the sample period.

Table E.1: Effective exchange rates – Percentage changes relative to the baseline projection

	Time horizon				
	1	3	5	10	20
U.S. Dollar	0.18	5.93	10.55	17.94	26.56
Pound Sterling	-0.00	-0.08	-0.15	-0.50	-1.30
Japanese Yen	0.14	5.10	7.85	16.47	34.41
Deutsche Mark	0.00	0.05	0.11	0.29	0.31
Turkish Lira	0.21	5.05	10.64	20.77	42.73

Notes: Comparison of exchange rates based on extrapolations of the conditioning variable relative to projections based on no-change extrapolations for variables and coefficients.

Figure E.17: United States



(a) Conditioning Variable

(b) Long-Run Coefficients

(c) Adjustment Coefficients

(d) Explanatory Variables

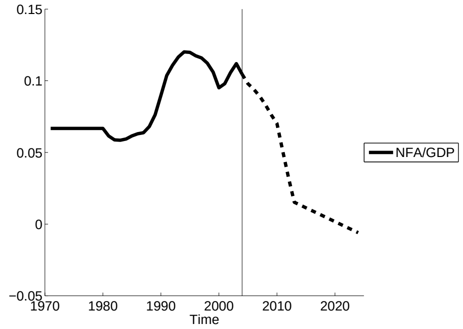
(e) Common Effect

(f) Nominal Exchange Rate

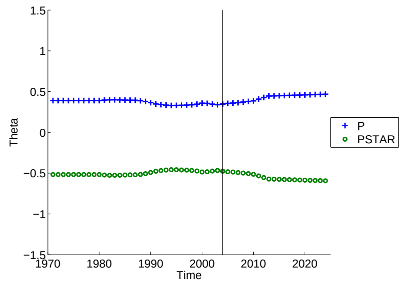
(g) Real Exchange Rate

Notes: Values right to the vertical line are based on projections. For exchange rates, the green line (•) denotes long-run projections based on extrapolations of all variables, the red line (×) represents long-run projections based on extrapolations of the conditioning variable only, and the blue line (+) denotes projections without changes in any variable.

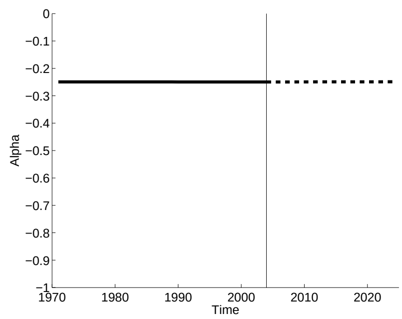
Figure E.18: Germany



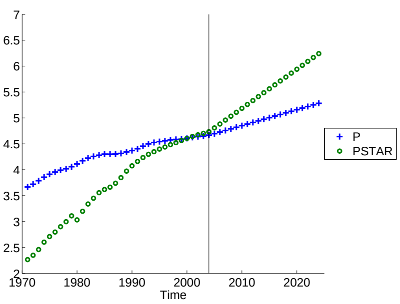
(a) Conditioning Variable



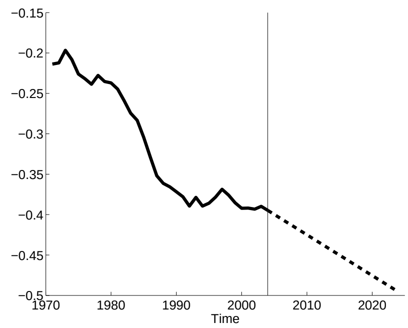
(b) Long-Run Coefficients



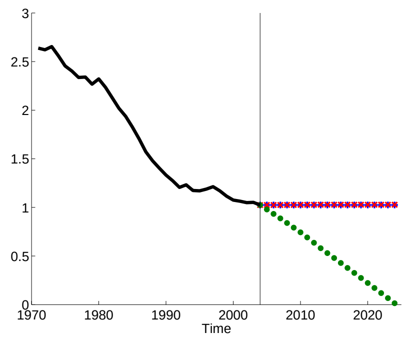
(c) Adjustment Coefficients



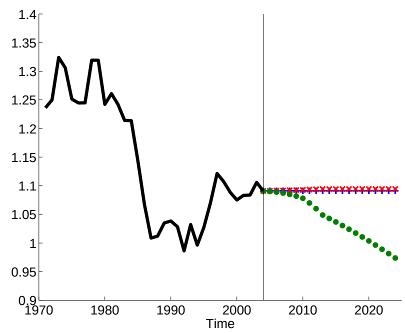
(d) Explanatory Variables



(e) Common Effect



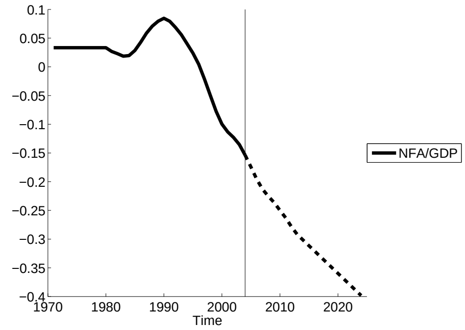
(f) Nominal Exchange Rate



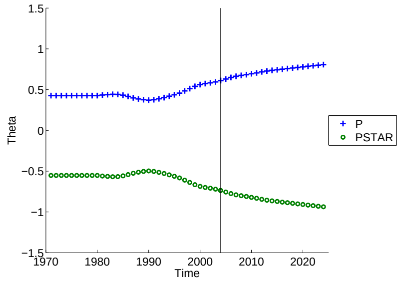
(g) Real Exchange Rate

Notes: See above.

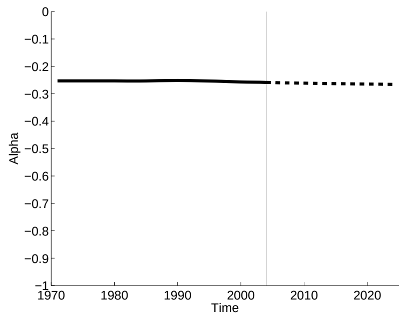
Figure E.19: United Kingdom



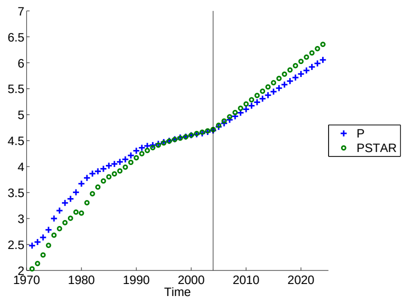
(a) Conditioning Variable



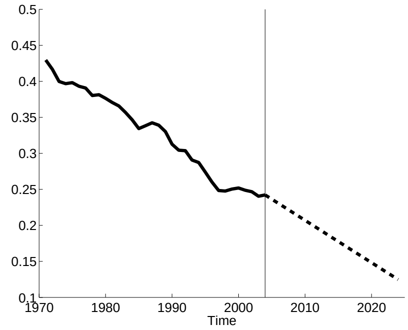
(b) Long-Run Coefficients



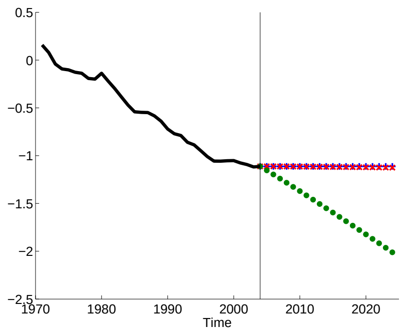
(c) Adjustment Coefficients



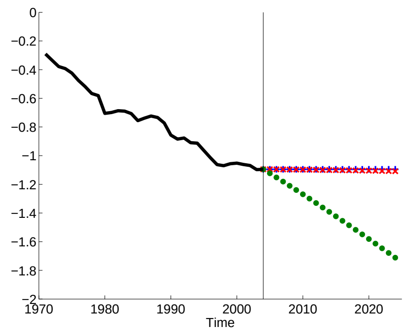
(d) Explanatory Variables



(e) Common Effect



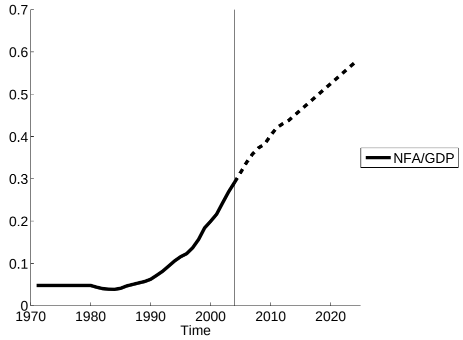
(f) Nominal Exchange Rate



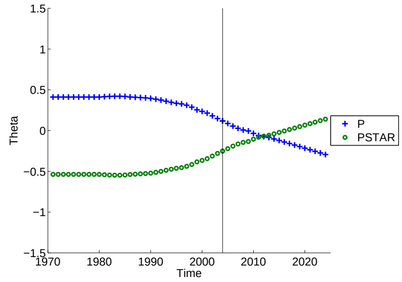
(g) Real Exchange Rate

Notes: See above.

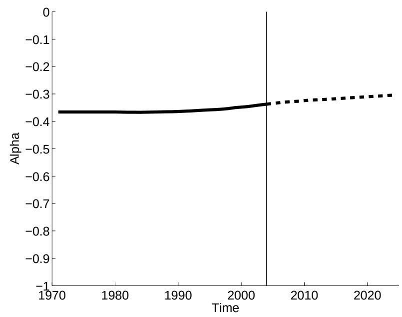
Figure E.20: Japan



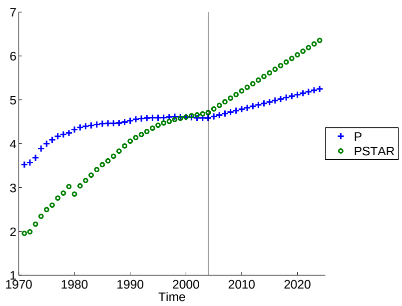
(a) Conditioning Variable



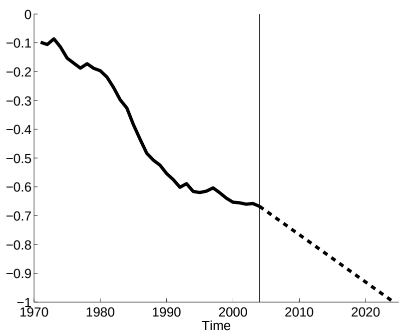
(b) Long-Run Coefficients



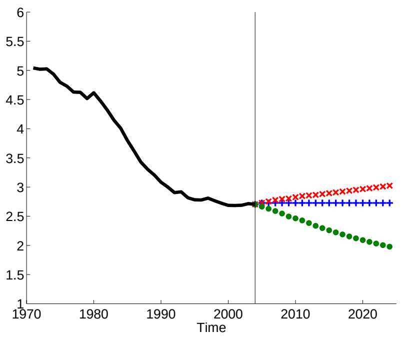
(c) Adjustment Coefficients



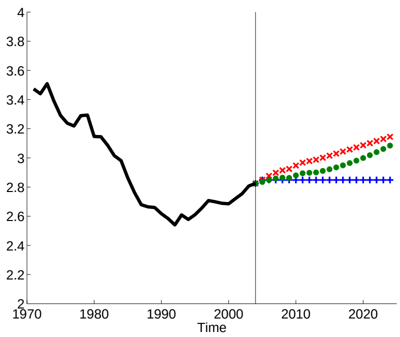
(d) Explanatory Variables



(e) Common Effect



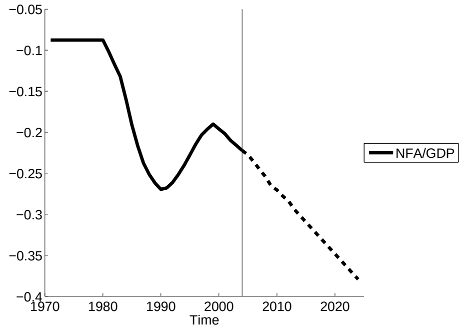
(f) Nominal Exchange Rate



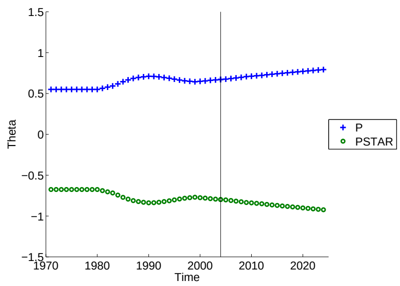
(g) Real Exchange Rate

Notes: See above.

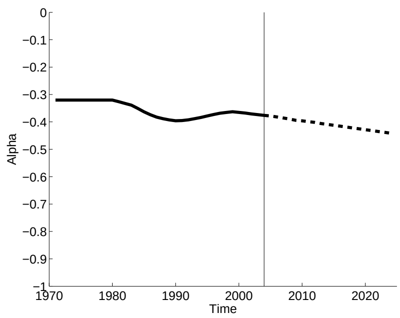
Figure E.21: Turkey



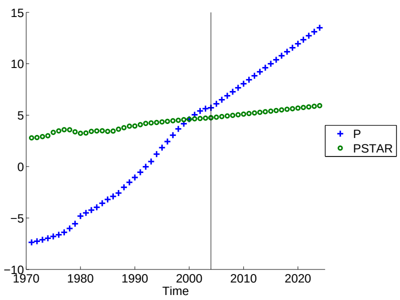
(a) Conditioning Variable



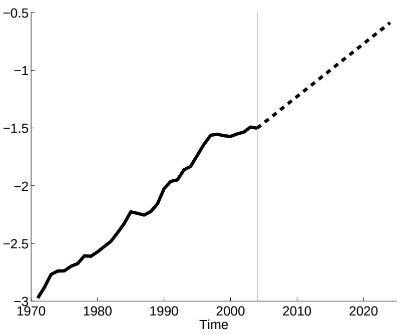
(b) Long-Run Coefficients



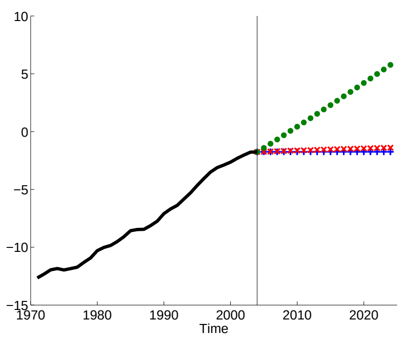
(c) Adjustment Coefficients



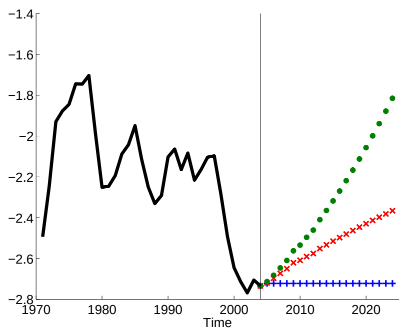
(d) Explanatory Variables



(e) Common Effect



(f) Nominal Exchange Rate



(g) Real Exchange Rate

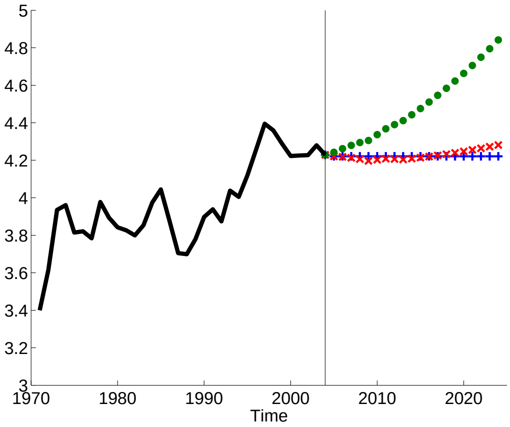
Notes: See above.

Table E.2: Bilateral exchange rates – Percentage changes relative to the baseline projection

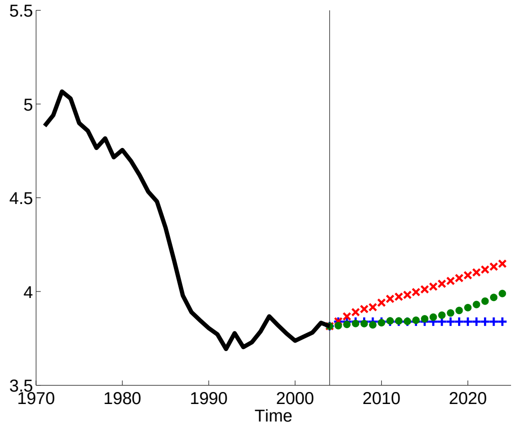
	Time horizon				
	1	3	5	10	20
Pound Sterling/U.S. Dollar	-0.18	-5.67	-9.68	-15.63	-22.01
Japanese Yen/U.S. Dollar	-0.04	-0.79	-2.45	-1.25	6.20
Japanese Yen/Pound Sterling	0.14	5.18	8.01	17.05	36.18
Deutsche Mark/U.S. Dollar	-0.18	-5.56	-9.45	-14.97	-20.74
Deutsche Mark/Pound Sterling	0.00	0.12	0.26	0.79	1.63
Deutsche Mark/Japanese Yen	-0.14	-4.81	-7.17	-13.89	-25.37
Turkish Lira/U.S. Dollar	0.03	-0.83	0.08	2.39	12.78
Turkish Lira/Pound Sterling	0.21	5.13	10.81	21.37	44.62
Turkish Lira/Japanese Yen	0.07	-0.05	2.59	3.69	6.19
Turkish Lira/Deutsche Mark	0.21	5.00	10.52	20.42	42.30

Notes: See above.

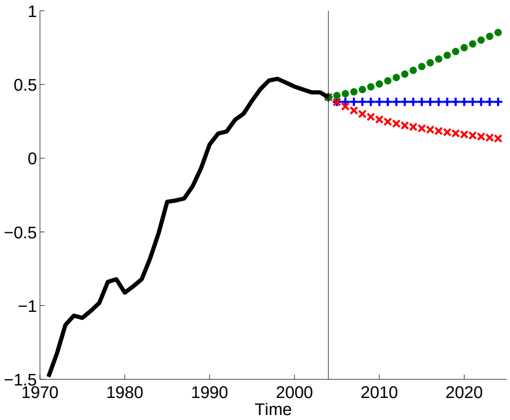
Figure E.22: Bilateral nominal exchange rates (I)



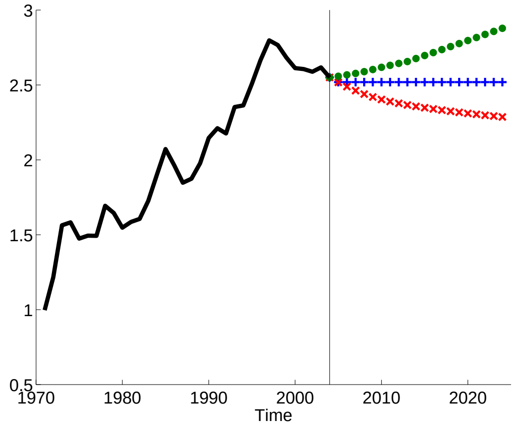
(a) Japanese Yen/U.S. Dollar



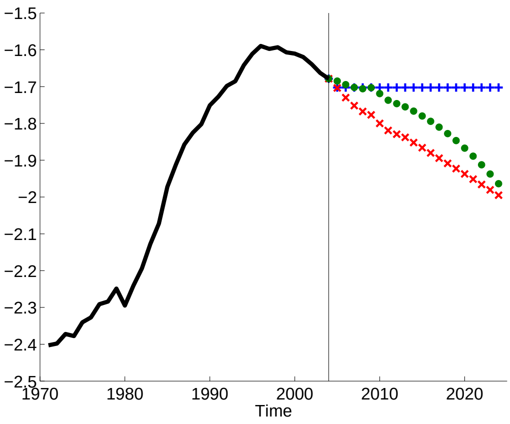
(b) Japanese Yen/Pound Sterling



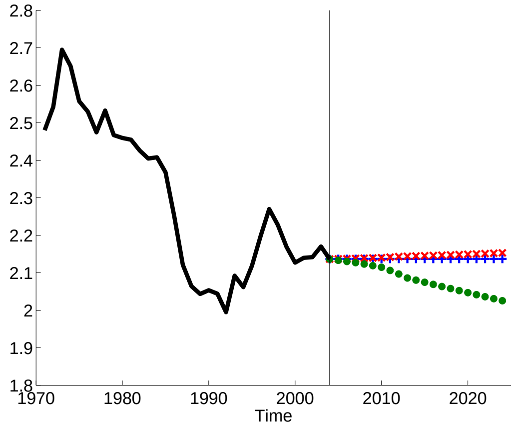
(c) Pound Sterling/U.S. Dollar



(d) Deutsche Mark/U.S. Dollar



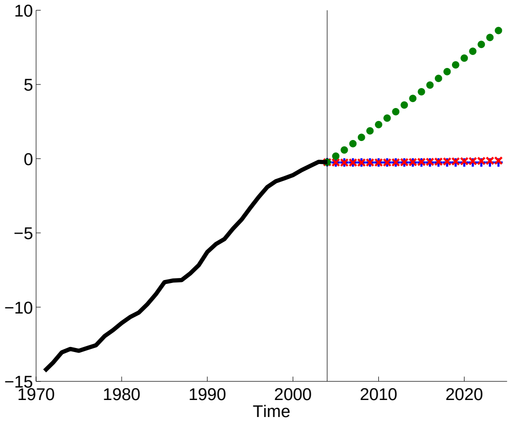
(e) Deutsche Mark/Japanese Yen



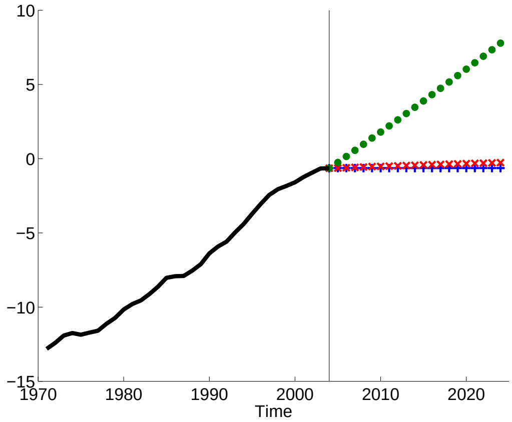
(f) Deutsche Mark/Pound Sterling

Notes: See above.

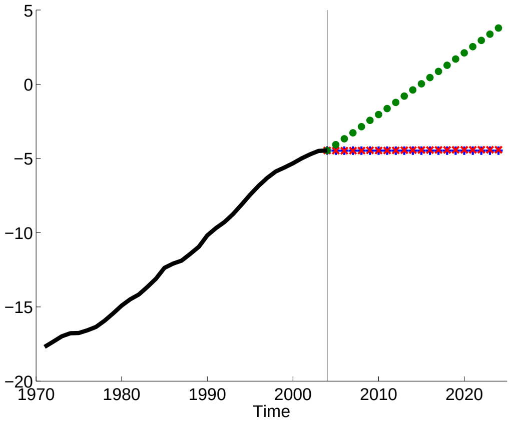
Figure E.23: Bilateral nominal exchange rates (II)



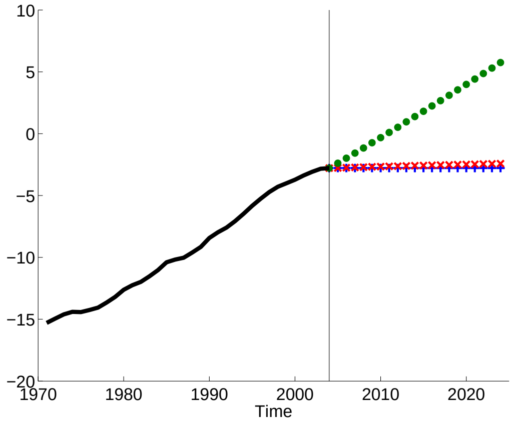
(a) Turkish Lira/U.S. Dollar



(b) Turkish Lira/Pound Sterling



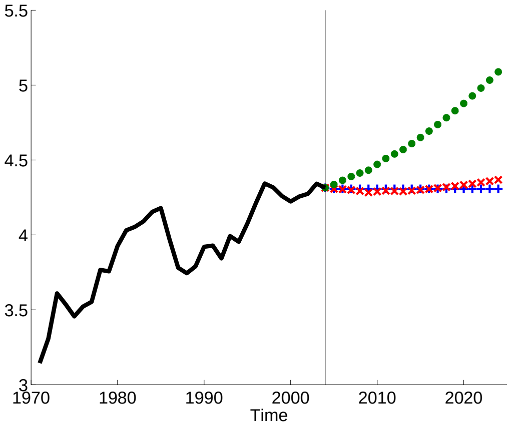
(c) Turkish Lira/Japanese Yen



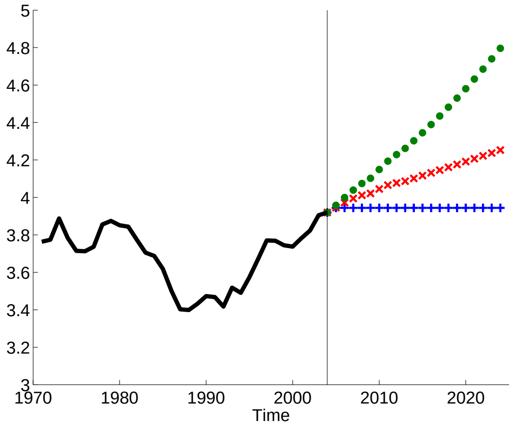
(d) Turkish Lira/Deutsche Mark

Notes: See above.

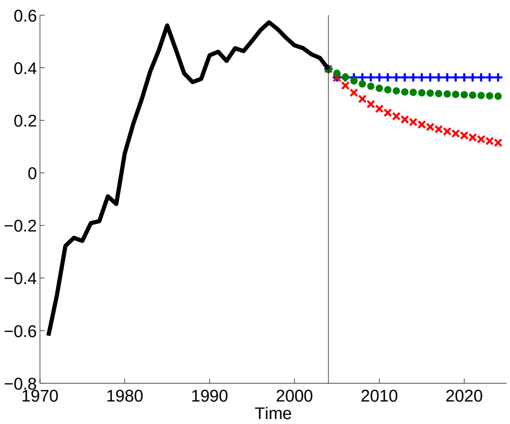
Figure E.24: Bilateral real exchange rates (I)



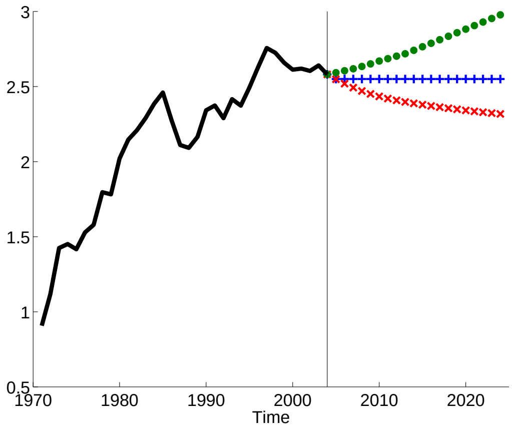
(a) Japanese Yen/U.S. Dollar



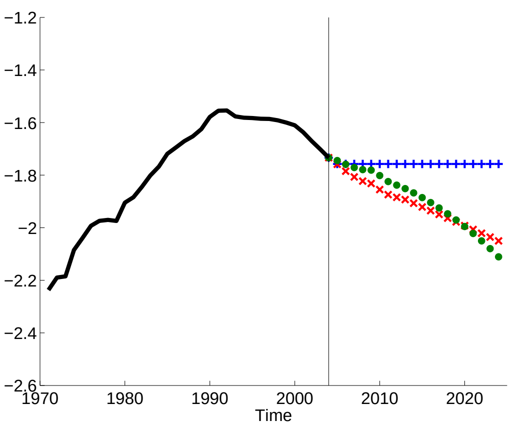
(b) Japanese Yen/Pound Sterling



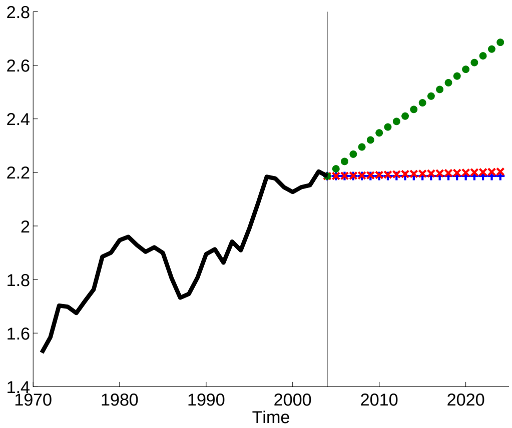
(c) Pound Sterling/U.S. Dollar



(d) Deutsche Mark/U.S. Dollar



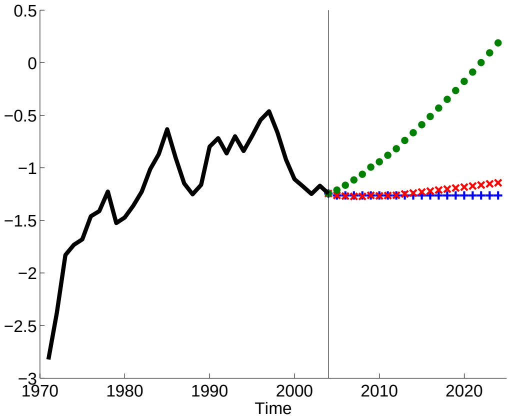
(e) Deutsche Mark/Japanese Yen



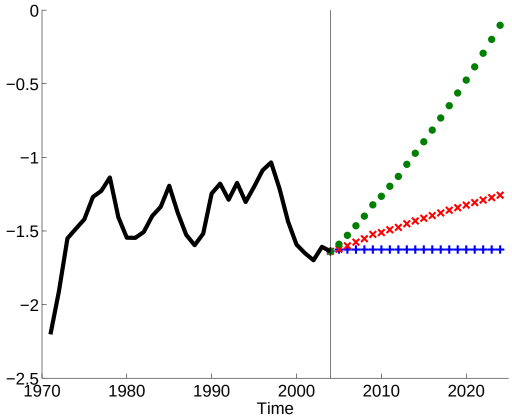
(f) Deutsche Mark/Pound Sterling

Notes: See above.

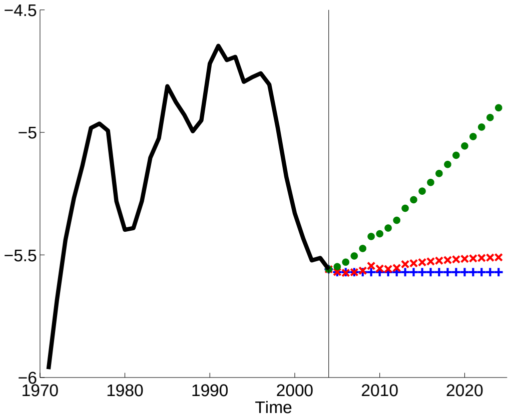
Figure E.25: Bilateral real exchange rates (II)



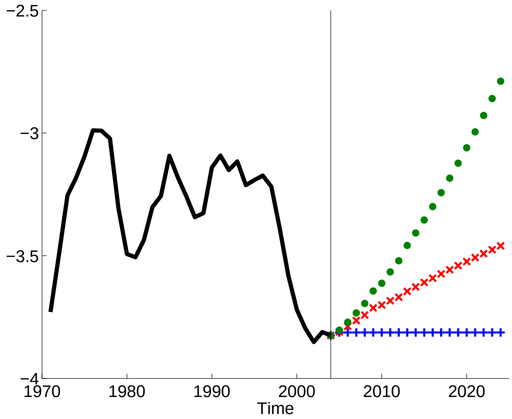
(a) Turkish Lira/U.S. Dollar



(b) Turkish Lira/Pound Sterling



(c) Turkish Lira/Japanese Yen



(d) Turkish Lira/Deutsche Mark

Notes: See above.

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