On the Degree of Homogeneity in Dynamic Heterogeneous Panel Data Models

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Abstract

We propose a semi-parametric approach to heterogeneous dynamic panel data modelling. The method generalizes existing approaches to model cross-section homogeneity within such panels. It allows for partial influence of other cross-section units on estimated coefficients, differentiating between short-run and long-run homogeneity, and determines the optimal degree of such homogeneity. The issue of cross-section homogeneity emerges as a special case of categorical conditioning. Applying our model to equilibrium exchange rate determination in a cross-country panel, we find evidence of largely heterogeneous adjustment and more homogeneous long-run coefficients across countries. The coefficient heterogeneity appears largely idiosyncratic and is not captured by simple categorizations like exchange rate regime classification.

Keywords: Dynamic Panel Data Models; Coefficient Homogeneity; Non-parametric Estimation, Equilibrium Exchange Rates.

JEL Classification: C23; F31; C52.

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1 Introduction

In many situations, the use of a panel data set confronts the empirical researcher with the problem of choosing the appropriate relationship between the panel's cross-section units. Such a situation typically arises in empirical macroeconomics when a variable of interest featuring a moderately sized time dimension shall be investigated within a say, multi-country framework. Noting that countries are often fairly different with respect to both endogenous and exogenous dynamics leads to a heterogenous specification. However, a fully heterogeneous model limits the use of a panel data set by basing estimates mostly on each country's individual time series observations.[1] One approach to this problem has been proposed by Pesaran, Shin and Smith (1999): they specify the model in such a way that almost all coefficients are heterogeneous except for those of a "deep", unquestionably homogeneous relationship, typically a cointegrating relationship.

Binder and Offermanns (2014) propose a framework where the researcher can take a medium position between these alternatives: coefficients represent either parametric or nonparametric functions of an underlying variable (the "indicator") which are estimated accordingly and thus, determine the degree of homogeneity endogenously. In the present paper, we elaborate on the nonparametric specification. In particular, we examine the capability of this approach to deliver a measure for the degree of homogeneity within a panel data model across the dimension that is determined through the choice of the indicator. We do so within the framework of estimating long-run equilibrium exchange rates and the speed of adjustment towards this equilibrium.

In contrast to Binder and Offermanns (2014), we consider the situation of a categorical indicator as suggested e.g. in Li, Ouyang and Racine (2013). Such a choice has the advantage that the bandwidth parameter of the kernel estimator which is bounded between zero and one, can be interpreted as the degree of homogeneity along the dimension of the indicator. Hence, we can easily compare homogeneity of the panel data with respect to different indicators. Second, the issue of cross-section homogeneity discussed above can be addressed in this framework as the special case of a nominally scaled indicator which is equivalent to the country identifier.

This issue has attracted particular attention in the context of equilibrium exchange rates (see the discussion in the following section). By generalizing the degree of homogeneity among countries and determining its optimal value, we are able to address two important aspects in heterogeneous exchange rate panels: first, we obtain efficient estimates of the mean relationship among the variables in the panel as cross-section observations are pooled

[1] Still, there could be other advantages of using the panel dimension even with fully heterogeneous coefficients, e.g. in a seemingly unrelated regression setup or by modelling cross-section dependence through a common factor structure, see e.g. Pesaran (2006).

as much as possible, but not too much to lose consistency. Second, potential clusters of coefficient estimates given the optimal degree of homogeneity can be used to draw inference on the optimal composition of largely homogeneous sub-groups of countries within the panel.

The remainder of this paper is organized as follows: Section 2 discusses the relation of our study to existing approaches, both with respect to the modelling and estimation methodology and the empirics of exchange rate dynamics. Section 3 presents the model, the estimation approach used, and the procedure to infer the optimal degree of homogeneity along the specificed indicator dimension. Section 4 contains the empirical application, i.e. it introduces the data used and the empirical specification and it presents the estimation results. Finally, Section 5 concludes.

2 Field of Study

The econometric model suggested in this paper is related to the field of dynamic heterogeneous panel data modelling as well as non-parametric estimation. In the broad field of panel data models, we are dealing with a situation where the time dimension T is large enough to enable cross-section specific estimation, but efficiency gains could be achieved if pooling of cross-section observations was possible. The cross-section dimension N is assumed to be fixed, but too large to allow for a seemingly unrelated regression (SUR) model. Such situations very often arise in the context of macroeconomic cross-country analyses using monthly, quarterly or annual observations over a couple of decades as well as observations for a significant share of countries available e.g. in data bases like the International Financial Statistics (IFS) of the International Monetary Fund (IMF), the Penn World Tables or others.

Pesaran and Smith (1995) show that within the framework of a random coefficients model, falsely imposing homogeneity across units on coefficients of a panel model leads to a biased estimate of the size of the average or "panel" effect of a variable on another. In this situation, it is safer to obtain the panel relationship between the variables from a cross-section average of individual estimates. If we were able to increase the degree of homogeneity in the estimation by an amount just to retain unbiasedness of the estimate but use correlated information from other units, this should increase efficiency and lower coefficient uncertainty. The limiting case to this approach is the fixed-effects model which assumes full homogeneity of all coefficients apart from the constant.

Using a fixed coefficients model, Pesaran et al. (1999) suggest an intermediate case by differentiating between different types of slope coefficients, for which homogeneity is more or less plausible, viz. long-run and short-run coefficients, respectively. However, although non-linearly connected, the decision for each of these types of coefficients still has to be made between full heterogeneity and full homogeneity. This paper suggests a method for generalizing the degree of homogeneity of coefficients to the continuous interval between zero and one. We use the main arguments by Pesaran et al. (1999) to also differentiate this degree of homogeneity between short-run and long-run coefficients.

Our work is related to research on testing for coefficient homogeneity in panel data models, e.g. by Swamy (1970), Pesaran and Yamagata (2008) and Breitung, Roling and Salish (2013), who developed tests for different magnitudes of N and T. However, these studies are essentially based on a random coefficient specification of the parameters under regard. Such an approach might not be well-suited to the case of macroeconomic cross-country data. First, interpretation and inference on the estimated coefficient for a specific country is impeded as this estimate is only one realization from the distribution across all countries, such that measures like the coefficient standard error are not easily interpretable. Second, it is not straightforward how to generalize the test statistics suggested there to the case when coefficient variation is driven by an underlying factor or indicator. The cross-section identifier would be such an indicator on a nominal scale, but other indicators, also on ordinal or metric scales, are imaginable and could lend economic interpretation to country differences.

In order to address these issues and also to generalize the degree of homogeneity of coefficients, we draw on approaches from the literature on non-parametric estimation of varying-coefficient models. In particular, we use the specification in Li, Ouyang and Racine (2013) dealing with categorical, i.e. nominal or ordinal conditioning information and translate it to the case of our dynamic heterogeneous panel data model. The choice of using only categorical information has the advantage that the bandwidth parameter in the kernel function, which is crucial to non-parametric modelling, can be interpreted as the degree of homogeneity along the specified dimension (e.g. the cross section), as it indicates the amount of information from other categories included in the estimation of a single coefficient. For the estimation itself, we follow the approaches by Fan and Zhang (1999) and Kumar and Ullah (2000).

We apply the suggested method to the issue of heterogeneity in adjustment and level of equilibrium exchange rates among countries. The fundamental value of the nominal exchange rate will be determined by consumer prices domestic and abroad. Hence, our analysis also contributes a variant to the broad empirical literature of testing purchasing power parity (PPP) of exchange rates. Most of this literature used real exchange rates as a special case of the price-based fundamental equilibrium value and applied panel unit root tests to these data. The overall picture is that these tests are able to reject non-stationarity of real exchange rates, at least for a significant fraction of the countries in the respective panel data set, although at relatively low values for the speed of adjustment to equilibrium, see e.g. Frankel and Rose (1996), Taylor and Sarno (1998), Papell and Theodoridis (1998), Murray and Papell (2005), Chortareas and Kapetanios (2009), to name only a few. However, country-specific details in this picture vary considerably.

Given the overall consensus of a half-life of shocks to PPP between three and five years surveyed by Rogoff (1996), several studies have documented substantial cross-country differences. Cheung and Lai (2000) report slightly lower, but more dispersed values for low to middle income countries,[2] while those for high income countries are more or less in accordance with the consensus. Papell (1997) finds that adjustment to equilibrium occurs faster for countries in the European Monetary System than for other industrialized countries. Holmes (2001) reports that evidence of PPP is weaker in high inflation than in low inflation countries (whereas Cheung and Lai (2000) finds the opposite relation). Alba and Papell (2007) and Wu, Cheng and Hou (2011) substantiate differences in the speed of adjustment of real exchange rates across countries. They apply panel unit root tests to country sub-groups that have been shaped to feature similar characteristics. Koedijk, Tims and van Dijk (2011) point out the importance of accounting for heterogeneous mean-reversion in the panel unit root test procedure. However, their approach is based on SUR estimation techniques and thus, limited to cases of small N panels.

We go beyond this work by allowing not only the speed of adjustment to equilibrium, but also the equilibrium itself be heterogeneous along the cross-section (or other categorical) dimension and still using poolability as far as possible. The domain of observations to be included in the estimation is not constrained in advance by pre-selection of country groups, but in principle covers the whole cross-section dimension, which is particularly important when short-run and long-run coefficients are subject to different homogeneity assumptions.

3 The Model

3.1 Error-Correction with State Dependent Homogeneity of Coefficients

Consider the following model for the relationship between variable y_{it} and the vector of variables $\boldsymbol{x}_{it}$, expressed in error-correction representation,

$$\Delta y_{it} = \alpha(z_{it})\Big[y_{i,t-1} - \boldsymbol{\theta}(z_{it})'\boldsymbol{x}_{i,t-1}\Big] + \boldsymbol{\delta}(z_{it})'\boldsymbol{w}_{it} + \varepsilon_{it} \tag{1}$$

for cross-section unit $i = 1, 2, ..., N$ and time period $t = 1, 2, ..., T$, where the parameters α, $\boldsymbol{\theta}$ and $\boldsymbol{\delta}$ are fixed unknown functions of the state variable z_{it}.

Such state dependence might be modelled in various ways; in this paper, we are concerned with categorical state information in the sense that the variable z may assume countably many discrete states $z_{it} \in \mathcal{Z}_k = \{z_1, z_2, ..., z_k\}$, suggested e.g. by Li, Ouyang and Racine (2013). Their specification allows for both ordinally and nominally scaled state information.

[2] According to their estimates, half-lives of shocks vary between zero and four years for most of these countries, but may also reach values larger than ten years.

In most (economic) applications, the researcher's interest usually lies in a subset of the parameters, $\boldsymbol{\varphi} = (\alpha, \boldsymbol{\theta}')'$. This is due to the fact that (1) is particularly used in cases where y_{it} and $\boldsymbol{x}_{it}$ are cointegrated such that $\boldsymbol{\theta}$ represents long-run coefficients and α the speed of adjustment coefficient.[3] On the other hand, $\boldsymbol{\delta}$ collects a number of coefficients on other regressors mainly required for the statistical appropriateness of the model, most importantly a constant as well as lagged differences of the variables in order to ensure serially uncorrelated zero-mean errors, such that we are able to assume ε_{it} representing a white noise process with constant variance σ_i^2. We also assume that potential correlation of errors in the cross-section dimension can be sufficiently well captured by correlated effects augmentation proposed by Pesaran (2006), such that $\boldsymbol{w}_{it}$ may also contain cross-sectional means of all model variables.

The interest in coefficients corresponds to the ability of (economic) theory to predict certain values for these coefficients, and thus potential benefits of pooling them. In accordance with Pesaran et al. (1999), we focus on the degree of homogeneity in long-run coefficients, and in addition, in the speed of adjustment coefficient. Consequently, in what follows we will simplify (1) by assuming full cross-section heterogeneity of $\boldsymbol{\delta}$, i.e. $\boldsymbol{\delta}(z_{it}) = \boldsymbol{\delta}_i$, although the extension to the general case would be straightforward.

Apart from estimating the unknown function $\boldsymbol{\varphi}(z)$, one major interest also lies in estimating the average panel effect $\overline{\boldsymbol{\varphi}}$, which can be obtained by integrating the function over z, or in our discrete case, as

$$\overline{\boldsymbol{\varphi}} = \frac{1}{k} \sum_{z \in \mathcal{Z}_k} \boldsymbol{\varphi}(z)$$

In the current study, we will consider two types of information provided by the data set within the class of categorical indicators, viz. nominal information and ordinal information. First and most importantly, we investigate the case which corresponds to the original question of homogeneity along the cross-section dimension and which does not require any additional information beyond the variables y, $\boldsymbol{x}$ and $\boldsymbol{w}$. To that aim, we define the indicator set

$$\mathcal{Z}_N^{(cs)} = \{1, 2, ..., N\}, \quad z_{it} = i,$$

which follows a nominal scale, i.e. as typical in panel settings, the cross-sectional ordering of observations does not contain any information.

Second, we consider the case when information on each observation is available from outside the set of variables considered so far. If such information is given on nominal scale, the treatment of this case does not differ from the case before, so here we consider information which classifies the observations. To that aim, define the ordinal indicator set

$$\mathcal{Z}_r^{(class)} = \{1, 2, ..., r\},$$

where the ordering of observations carries information, but distances do not.

[3]For convenience, we will use this labeling irrespective whether the underlying variables are in fact integrated of order larger than zero.

3.2 Estimation Approach

In order to solve the problem that observations from other cross-section units shall be incorporated upon estimation of coefficients for a specific cross-section unit to a certain degree, we follow a non-parametric local least-squares approach which is standard in the literature (see e.g. Hastie and Tibshirani (1993) or Fan and Zhang (1999)) and estimate (1) by weighting all available observations across time and cross-section dimension using a kernel function and minimizing the following modified residual sum of squares:

$$\hat{\boldsymbol{\varphi}}(z,\lambda) = \underset{\boldsymbol{\varphi}}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} \varepsilon_{it}^2 \, \kappa(z_{it}|z,\lambda), \tag{2}$$

where $\kappa(z_{it}|z,\lambda)$ represents the kernel that determines to what extent an observation (i,t) with nonzero distance $z_{it} - z$ will be included in the estimation for given values of z and λ.

Apparently, the kernel functions have to differ along the cases described above, and they have to differ from the standard case of continuous metric indicator variables. We follow the suggestions by Li, Ouyang and Racine (2013) for the nominal and for the ordinal case. The nominal nature of the indicator set $\mathcal{Z}^{(cs)}$ is captured by the following kernel function

$$\kappa^{(cs)}(z_{it}|z,\lambda) = \begin{cases} 1 & \text{if } z_{it} = z \\ \lambda^{n_k} & \text{else} \end{cases}$$

while the ordinal nature of the indicator set $\mathcal{Z}^{(class)}$ is captured by the kernel function

$$\kappa^{(class)}(z_{it}|z,\lambda) = \lambda^{|z_{it}-z|}.$$

In both specifications, $0 \leq \lambda \leq 1$ since the border values correspond to the cases of full heterogeneity and full homogeneity along the specified indicator set, respectively. Consequently, the value of λ can be interpreted as the degree of homogeneity for the corresponding coefficient along this dimension. As we argued above, it appears advisable to differentiate between the degree of homogeneity for the speed of adjustment parameter α, λ_α, and the long-run coefficients $\boldsymbol{\theta}$, λ_θ.

In case of the nominal indicator, we introduce a scaling factor $n_k \geq 1$ which is increasing in the number of states present in the sample. In particular, we choose

$$n_k = \sqrt{k-1}.$$

This factor is needed to enable comparison of λ across panels with different cross-section dimension. Note that in large panels, without such scaling the observations for a specific category / cross-sectional unit will be dominated by the large number of observations from other categories / units even for small values of λ. The problem is less severe and will be neglected in the ordinal case, as observations from an increasing number of categories will have decreasing impact on the category under scrutiny.

Given that the error-correction model is non-linear in the long-run coefficients, we have to resort to iterative estimation techniques to solve (2). We follow the approach suggested by Breitung (2005) and apply a three-step estimation procedure. Hence, for any given degree of homogeneity $0 \leq \lambda_\alpha \leq 1$ and $0 \leq \lambda_\theta \leq 1$, we run the following algorithm for each $z \in \mathcal{Z}_k$:

1. Obtain initial estimates from linearized equation

$$\Delta y_{it} = \alpha(z_{it}|z, \underline{\lambda}) y_{i,t-1} + \boldsymbol{\beta}(z_{it}|z, \underline{\lambda})' \boldsymbol{x}_{i,t-1} + \boldsymbol{\delta}_i' \boldsymbol{w}_{it} + \varepsilon_{it} \tag{3}$$

   where $\boldsymbol{\beta}(z_{it}) = -\alpha(z_{it})\boldsymbol{\theta}(z_{it})$ and $\underline{\lambda} = \min(\lambda_\alpha, \lambda_\theta)$.

2. Estimate $\boldsymbol{\theta}(z, \lambda_\theta)$ given $\hat{\alpha}(z_{it})$ from

$$\Delta y_{it}/\hat{\alpha}(z_{it}) - y_{i,t-1} = -\boldsymbol{\theta}(z_{it}|z, \lambda_\theta)' \boldsymbol{x}_{i,t-1} + \boldsymbol{\delta}_i' \boldsymbol{w}_{it}/\hat{\alpha}(z_{it}) + \varepsilon_{it}/\hat{\alpha}(z_{it}) \tag{4}$$

3. Estimate $\alpha(z, \lambda_\alpha)$ given $\hat{\boldsymbol{\theta}}(z_{it})$ from

$$\Delta y_{it} = \alpha(z_{it}|z, \lambda)[y_{i,t-1} - \hat{\boldsymbol{\theta}}(z_{it})' \boldsymbol{x}_{i,t-1}] + \boldsymbol{\delta}_i' \boldsymbol{w}_{it} + \varepsilon_{it} \tag{5}$$

In each step, we use the LLSK estimator described in Appendix A with $\boldsymbol{\Upsilon}, \boldsymbol{\Xi}$ and $\boldsymbol{\Omega}^{-1}$ obtained from stacking the following matrices across i:

1. $\boldsymbol{\Upsilon}_i = \boldsymbol{M}_i \Delta \boldsymbol{y}_i, \quad \Xi_i = \boldsymbol{M}_i [\boldsymbol{y}_{i,-1} \;\; \boldsymbol{X}_{i,-1}], \quad \boldsymbol{\Omega}_i^{-1}(z, \underline{\lambda}) = \text{diag}_t\{\kappa(z_{it}|z, \underline{\lambda})\hat{\sigma}_i^{-2}\}$
2. $\boldsymbol{\Upsilon}_i = \boldsymbol{M}_i \widetilde{\Delta \boldsymbol{y}}_i - \boldsymbol{M}_i \boldsymbol{y}_{i,-1}, \quad \Xi_i = \boldsymbol{M}_i \boldsymbol{X}_{i,-1}, \quad \boldsymbol{\Omega}_i^{-1}(z, \lambda_\theta) = \text{diag}_t\{\kappa(z_{it}|z, \lambda_\theta)\hat{\alpha}^2(z_{it})\hat{\sigma}_i^{-2}\}$
3. $\boldsymbol{\Upsilon}_i = \boldsymbol{M}_i \Delta \boldsymbol{y}_i, \quad \Xi_i = \boldsymbol{M}_i \hat{\boldsymbol{\xi}}_{i,-1} \quad \boldsymbol{\Omega}_i^{-1}(z, \lambda_\alpha) = \text{diag}_t\{\kappa(z_{it}|z, \lambda_\alpha)\hat{\sigma}_i^{-2}\}$

where $\boldsymbol{M}_i = \boldsymbol{I}_T - \boldsymbol{W}_i(\boldsymbol{W}_i'\boldsymbol{W}_i)^{-1}\boldsymbol{W}_i'$, $\boldsymbol{W}_i = (\boldsymbol{w}_{i1} \; \boldsymbol{w}_{i2} \; \ldots \; \boldsymbol{w}_{iT})'$, $\Delta \boldsymbol{y}_i = (\Delta y_{i1} \; \Delta y_{i2} \; \ldots \; \Delta y_{iT})'$, $\widetilde{\Delta \boldsymbol{y}}_i = (\Delta y_{i1}/\hat{\alpha}(z_{i1}) \; \Delta y_{i2}/\hat{\alpha}(z_{i2}) \; \ldots \; \Delta y_{iT}/\hat{\alpha}(z_{iT}))'$, $\boldsymbol{y}_{i,-1} = (y_{i0} \; y_{i1} \; \ldots \; y_{i,T-1})'$, $\boldsymbol{X}_{i,-1} = (\boldsymbol{x}_{i0} \; \boldsymbol{x}_{i1} \; \ldots \; \boldsymbol{x}_{i,T-1})'$, $\hat{\boldsymbol{\xi}}_{i,-1} = (\hat{\xi}_{i0} \; \hat{\xi}_{i1} \; \ldots \; \hat{\xi}_{i,T-1})'$, $\hat{\xi}_{i,t-1} = y_{i,t-1} - \hat{\boldsymbol{\theta}}(z_{it})'\boldsymbol{x}_{i,t-1}$ and $\text{diag}_t(\cdot)$ means diagonalization along $t = 1, 2, ..., T$. Initial variances σ_i^2 are estimated from the linearized version of the model which is fully heterogeneous in the cross-section dimension, and are subject to an iterative procedure applied to Equation (3).

3.3 The Optimal Degree of Homogeneity

Given that different degrees of homogeneity λ for a set of parameters may imply different estimated average panel effects, but in any case implies different estimates for individual units' coefficients, we wish to determine the "optimal" value for λ that characterizes best the relationship among units in the panel. To do so, we follow the so-called "cross-validation approach" (see, e.g. Härdle and Marron, 1985; Li and Zhou, 2005; Li et al., 2013). We aim at measuring the "similarity" of panel units to each other. The approach works through a "leave-one-out" procedure, i.e. for each $z \in \mathcal{Z}_k$ we compute the estimated coefficient based on a sample which excludes this category z. The estimator is thus based on the information that we obtain from the other categories – the more homogeneous the units are, the better this estimator will capture the relation for the unit that was left out.

Formally, we compute the optimal λ as the mininimizer $\lambda^* = \text{argmin}\, CV(\lambda)$ to the following criterion

$$CV(\lambda) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left[\Delta y_{it} - \Delta \hat{y}_{it}(\lambda)\right]^2$$

where each forecast $\Delta \hat{y}_{it}$ is computed by applying the estimated coefficients from the other categories $z \neq z_{it}$ to the missing category,

$$\Delta \hat{y}_{it}(\lambda) = \widetilde{\alpha}(z_{it}|\lambda)\left[y_{i,t-1} - \widetilde{\boldsymbol{\theta}}(z_{it}|\lambda)'\boldsymbol{x}_{i,t-1}\right] + \hat{\boldsymbol{\delta}}_i'\boldsymbol{w}_{it}$$

We obtain these coefficients in the following way: for each $z_j \in \mathcal{Z}_k$, $j = 1, 2, ..., k$, compute the estimator based on all other categories $z \in \mathcal{Z}_k \backslash \{z_j\}$,

$$\hat{\boldsymbol{\varphi}}_{-j}(z, \lambda) = \underset{\boldsymbol{\varphi}}{\text{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} \varepsilon_{it}^2 \, \widetilde{\kappa}(z_{it}|z, z_j, \lambda),$$

and leave out the information from those observations associated with z_j:

$$\widetilde{\kappa}(z_{it}|z, z_j, \lambda) = \begin{cases} 0 & \text{if } z_{it} = z_j \\ \kappa(z_{it}|z, \lambda) & \text{else.} \end{cases}$$

Finally, we aggregate the information from all $z \neq z_j$ to obtain the estimator to be applied to category z_j:

$$\widetilde{\boldsymbol{\varphi}}(z_j|\lambda) = \mathrm{A}_{k-1}(\hat{\boldsymbol{\varphi}}_{-j}(z|\lambda))$$

with $\mathrm{A}_{k-1} : \mathbb{R}^{m \times (k-1)} \mapsto \mathbb{R}^m$. In case of nominal categories (like cross-section unit identifiers), there is no source of information beyond simple averaging, such that we specify A_{k-1} as the arithmetic mean and compute

$$\widetilde{\boldsymbol{\varphi}}^{(cs)}(z_j|\lambda) = \frac{1}{k-1} \sum_{z \neq z_j} \hat{\boldsymbol{\varphi}}_{-j}(z|\lambda).$$

In the case of ordinal categories, we might be able to exploit superior information from neighboring categories over more distant ones. In principle, a non-parametric function could be used here as well. In the application to be presented below, we specify the aggregating function as follows:

$$\widetilde{\boldsymbol{\varphi}}^{(class)}(z_j|\lambda) = \hat{\boldsymbol{a}}_j + \hat{\boldsymbol{b}}_j z_j$$

where $\hat{\boldsymbol{a}}_j$ and $\hat{\boldsymbol{b}}_j$ are the least-squares coefficient vectors from projecting $\hat{\boldsymbol{\varphi}}_{-j}(z|\lambda)$ onto a constant and z, respectively.

4 The Degree of Homogeneity in Equilibrium Exchange Rates

4.1 Empirical Specification

This study investigates the equilibrium adjustment of nominal exchange rates based on price fundamentals. We use quarterly data for up to 75 countries in the period 1970 I to 2012 IV, mostly obtained from the International Monetary Fund (IMF). In order to avoid sensitivity of our results with respect to the chosen base currency,[4] we employ a multilateral definition of our variables. Hence, our dependent variable is the natural logarithm of a country's effective exchange rate e_{it}, defined as the weighted average of the country's logged nominal exchange rate s_{ijt} vis-a-vis its trading partners, i.e.

$$e_{it} = \sum_{j=1}^{N} w_{ijt} s_{ijt}, \qquad \sum_{j=1}^{N} w_{ijt} = 1.$$

Data for spot exchange rates are taken from the IMF's International Financial Statistics (IFS) database. Bilateral weights are obtained as lagged smoothed time-varying relative exports plus imports as a share of country i's total sum of exports and imports. The trade matrices required for this computation have been obtained from the IMF's Direction of Trade Statistics. Information on prices is given by consumer price indices (CPI), seasonally adjusted, also taken from the IFS database. We compute "foreign prices", i.e. the price index referring to the country's aggregated trading partner, in an equivalent way as

$$p_{it}^{*} = \sum_{j=1}^{N} w_{ijt} p_{jt},$$

using the same weights as above.

In line with the empirical literature and supported by own panel unit root tests (not reported here), the variables e_{it}, p_{it} and p_{it}^{*} are treated as being integrated of order one. Consequently, the level relationship among these variables (if it exists) can be interpreted as a cointegrating relationship. Consequently, corresponding to the generic model (1), we estimate the following equation

$$\Delta e_{it} = \alpha(z_{it})[e_{i,t-1} - \theta_1(z_{it})p_{i,t-1} - \theta_2(z_{it})p_{i,t-1}^{*} - \rho_0(z_{it})] + \sum_{j=1}^{q_{0,i}} \delta_{0,j,i}\Delta e_{i,t-j} + \sum_{j=0}^{q_{1,i}} \delta_{1,j,i}\Delta p_{i,t-j} + \sum_{j=0}^{q_{2,i}} \delta_{2,j,i}\Delta p_{i,t-j}^{*} + \delta_{0,i} + \varepsilon_{it}$$

with lag orders $q_{0,i}$, $q_{1,i}$ and $q_{2,i}$ determined via the Akaike information criterion in the fully cross-sectional heterogeneous model.

[4] This sensitivity has been documented e.g. by Papell and Theodoridis (2001).

The equation describes the adjustment process towards the long-run equilibrium level of the nominal effective exchange rate based on price fundamentals. The price variables are modelled as being weakly exogenous to exchange rates. The long-run relationship is established only in case of $\alpha(z_i)$ being negative and significantly different from zero.[5] Since the variables are given in logs, we will refer to the parameters in the cointegrating relationship as the "long-run elasticity to domestic prices" (θ_1) and the "long-run elasticity to foreign prices" (θ_2), respectively. These elasticities as well as the speed of adjustment to equilibrium are potentially different across categories (e.g., units), but they become homogeneous for $\lambda \to 1$. As a special case, strict (conditional) purchasing power parity (PPP) emerges if

$$\theta_1(z_{it}) = 1 \quad \text{and} \quad \theta_2(z_{it}) = -1$$

for some z_{it} (and $\alpha(z_{it}) < 0$ for the same z_{it}).

The model includes the usual cross-section specific constant to account for incidental fixed effects. Furthermore, we introduce a constant in the long-run relationship which is not identified without additional assumptions. This constant serves the role of preventing a structural break (mean shift) in the cointegrating relationship induced by changes in the parameters θ_1 and θ_2 due to changes in the conditioning variable z_{it}. Hence, we identify $\rho_0(z_{it})$ as the mean of $e_{i,t-1} - \theta_1(z_{it})p_{i,t-1} - \theta_2(z_{it})p^*_{i,t-1}$ for each z.

Errors ε_{it} are assumed to be white noise and also uncorrelated along the cross-section dimension as laid out in the previous section. However, we refrain from including cross-sectional averages of the model variables into the equation for the following reason: the variable p^*_{it}, although cross-section specific, is constructed as a weighted average across all countries. Empirically, it is largely common to most of the countries and thus, yields a reasonably well approximation to the common factor. Including a cross-sectional average of this variable induces the problem of multicollinearity to the estimation.[6]

For the (nominal) case of homogeneity along the cross-section dimension, we define four groups of countries with perceived geographic and/or economic proximity in order to alleviate the computational burden induced by a large number of categories to be evaluated. These groups are called "OECD countries" comprising Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Korea, Mexico, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom and United States; "East Asian countries" comprising Bangladesh, Hong Kong, India, Indonesia, Sri Lanka, Malaysia, Myanmar, Nepal, Pakistan, the Philippines, Singapore and Thailand; "South American countries" comprising Argentina, Bolivia, Brazil, Colombia, Costa Rica, Dominican Republic, El

[5] Upon interpretation of results, we will have to take account of the fact that the least-squares estimator for α has a non-standard distribution.

[6] The problem is aggrevated when considering also the cross-sectional average of p_{it} and lagged differences of both variables.

Salvador, Guatemala, Honduras, Haiti, Jamaica, Panama, Peru, Paraguay and Uruaguay as well as "African (Developing) Countries" comprising Angola, Burundi, Burkina Faso, Cameroon, Central African Republic, Chad, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Ghana, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Mauritania, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sudan, Swaziland, Togo, Uganda and Zambia. Hence, for each group g with number of countries N_g, we specify the nominal indicator as the country index, i.e.

$$\mathcal{Z}_{N_g}^{(cs)} = \{1, 2, ..., N_g\}.$$

For the ordinal case, we investigate the effect of the exchange rate regime on the equilibrium and adjustment to equilibrium of exchange rates. The empirical information on *de facto* exchange rate regimes for each country in each year is obtained from the data by Levy-Yeyati and Sturzenegger (2005), implying that this variable is available only up to the year 2004. The authors classify a country's nominal exchange rate as belonging to one of the categories "flexible", "dirty float", "crawling peg", "fixed" and "inconclusive". Since their classification is based on a cluster analysis and the last category contains elements of both, flexible and fixed exchange rates, our specification puts this category to a middle position and assigns the following ordinal indicator:

$$\mathcal{Z}_5^{class} = \{1 = \text{flexible},\ 2 = \text{dirty float},\ 3 = \text{inconclusive},\ 4 = \text{crawling peg},\ 5 = \text{fixed}\}.$$

The ordinal nature of this classification for our purpose is motivated by the findings e.g. by Cheung and Lai (2000) that evidence in favor of PPP is stronger for fixed than for flexible exchange rates. Hence, with our model we are able to investigate the hypothesis that the equilibrium relationship and the speed of adjustment towards this equilibrium are monotonous functions in the degree of exchange rate flexibility.

In both cases, we allow for different degrees of homogeneity for long-run elasticities (λ_θ) and for short-run adjustment (λ_α). We estimate the model for six different values (0, 0.25, 0.35, 0.55, 0.85 and 1) for each type, such that we have 36 combinations in total.

4.2 Estimation Results

The estimation results for the case of homogeneity along the cross-section dimension are depicted in Tables 1 to 4 as well as in Figures B.1 to B.12 in Appendix B. The tables show the estimated panel effects for the three coefficients under regard for all country groups. Since the degree of homogeneity can differ between speed of adjustment parameter and long-run coefficients, we show the four different outcomes for each type of coefficient given the optimal degree of homogeneity for the other type of coefficient. These optimal values for

λ_α and λ_θ, respectively, are highlighted via bold-face coefficient estimates. Standard errors of panel coefficients have been obtained via the Delta method.

Comparing the results across groups, we note that in all but one case, the optimal degree of homogeneity for the long-run coefficients is higher than for the short-run speed of adjustment parameter, supporting the arguments brought forward e.g. by Pesaran et al. (1999). Only the East Asian countries feature a lower degree of long-run relative to short-run homogeneity.

Table 1: Panel Effects, 22 OECD Countries, 1970–2012

	$\lambda = 0$	$\lambda = 0.35$	$\lambda = 0.55$	$\lambda = 1$
$\bar{\alpha}$	−0.081	**−0.071**	−0.062	−0.061
	(0.006)	**(0.005)**	(0.002)	(0.001)
$\bar{\theta}_1$	0.522	0.901	**0.929**	0.933
	(0.120)	(0.008)	**(0.003)**	(0.002)
$\bar{\theta}_2$	−0.687	−0.932	**−0.957**	−0.960
	(0.087)	(0.013)	**(0.006)**	(0.003)

Notes: Speed of adjustment parameters and long-run elasticities as functions of the degree of homogeneity, given optimal degree for the other coefficients. Bold-face numbers represent optimal values according to cross-section validation. Standard errors in parentheses below coefficients.

Table 2: Panel Effects, 12 East Asian Countries, 1970–2012

	$\lambda = 0$	$\lambda = 0.35$	$\lambda = 0.55$	$\lambda = 1$
$\bar{\alpha}$	−0.083	−0.042	**−0.036**	−0.034
	(0.018)	(0.004)	**(0.002)**	(0.002)
$\bar{\theta}_1$	0.471	**0.926**	0.815	0.811
	(0.146)	**(0.058)**	(0.057)	(0.047)
$\bar{\theta}_2$	−0.363	**−0.864**	−0.830	−0.832
	(0.168)	**(0.052)**	(0.055)	(0.046)

Notes: See Table 1.

Furthermore, in case of the OECD and the East Asian countries, the optimal degrees of homogeneity also for long-run coefficients are substantially lower than one. Even in the other groups, the long-run elasticities are not always largest in the fully homogeneous case, indicating that evidence in favor of PPP is not always stronger, the more homogeneity is imposed on the coefficients in the estimation procedure.

In terms of coefficient magnitudes, the elasticity to domestic prices in most cases is larger than to foreign prices. The interpretation of these coefficients as cointegration parameters is granted by the estimated speed of adjustment being negative throughout and strongly significant.[7] However, in most cases the hypothesis of strict PPP cannot be substantiated.

Table 3: Panel Effects, 15 South American Countries, 1970–2012

	$\lambda = 0$	$\lambda = 0.35$	$\lambda = 0.55$	$\lambda = 1$
$\bar{\alpha}$	−0.069	−0.042	**−0.029**	−0.026
	(0.009)	(0.004)	**(0.002)**	(0.001)
$\bar{\theta}_1$	0.860	0.942	0.938	**0.940**
	(0.141)	(0.006)	(0.007)	**(0.005)**
$\bar{\theta}_2$	−0.851	−0.869	−0.857	**−0.853**
	(0.238)	(0.011)	(0.010)	**(0.008)**

Notes: See Table 1.

Table 4: Panel Effects, 26 African Countries, 1970–2012

	$\lambda = 0$	$\lambda = 0.35$	$\lambda = 0.55$	$\lambda = 1$
$\bar{\alpha}$	**−0.079**	−0.056	−0.034	−0.030
	(0.009)	(0.005)	(0.002)	(0.001)
$\bar{\theta}_1$	0.174	0.975	0.991	**0.997**
	(0.114)	(0.006)	(0.002)	**(0.001)**
$\bar{\theta}_2$	−0.238	−0.873	−0.832	**−0.823**
	(0.239)	(0.016)	(0.005)	**(0.003)**

Notes: See Table 1.

The graphs in Figures B.1 to B.12 present details for the estimated coefficients for each unit within the groups. For sake of clarity and readability, standard errors are not depicted. In all cases apart from the group of African countries, country identifiers are shown right to the graph in the order of magnitudes of the respective coefficient at $\lambda = 0$. Again, estimated coefficients are shown as a function of the degree of homogeneity used for estimating this type of coefficients, given optimal degree of homogeneity used for the other type of coefficients. A bold vertical line denotes the optimal value for λ according to cross-validation.

The graphs indicate the paths of coefficient estimates towards full cross-section homogeneity. First, we see that especially for the OECD countries, estimated long-run elasticities are largely homogeneous already for incomplete imposed homogeneity, whereas in most other cases, estimates are still fairly diverse. Second, we see that using even a small amount of

[7] Even though the distribution of this coefficient is non-standard, this interpretation appears safe given that the point estimates are around ten times larger than the standard errors.

information from other countries is able to change magnitudes of coefficients drastically. Often, even the initial ordering of coefficient magnitudes does not persist when λ increases.

Third, these graphs in some cases enable assessing the role of a country or a sub-group of countries in comparison to the other countries within the specified group. Consider e.g. the speed of adjustment coefficient for East Asian countries in Figure B.4. The estimates suggest that Hong Kong exhibits a lower speed of adjustment towards equilibrium than the rest of the group, and that the latter might even feature a higher degree of homogeneity if Hong Kong was taken out of the group. Hence, the analysis can also be used to shape groups or clusters of countries with relatively high degree of homogeneity.

Overall, the empirical results from this analysis indicate that in most cases both, the equilibrium relation and the adjustment towards equilibrium are cross-section dependent. However, with increasing λ, estimates converge to values around those implied by PPP. Hence, imposing the optimal degree of homogeneity, which is not necessarily equal to one, might help in uncovering the fundamental value of the exchange rate.

Given the finding of limited cross-section homogeneity, we can now use our model to investigate potential causes for this variation. In particular, countries could behave similar with respect to exchange rate dynamics because they find themselves at least temporarily in the same economic environment or regime. Hence, in the following step we investigate whether long-run and/or short-run coefficients are functions of the exchange rate regime, using the indicator defined as $\mathcal{Z}_5^{(class)}$ above. We use the whole group of countries in one panel specification. However, due to lack of exchange rate regime data for some of the countries, the number of available countries has reduced to 66.

Table 5: Panel Effects, FX Regimes: 66 Countries, 1970–2004

	$\lambda = 0$	$\lambda = 0.35$	$\lambda = 0.55$	$\lambda = 1$
$\bar{\alpha}$	0.002	-0.002	-0.005	$\mathbf{-0.004}$
	(0.005)	(0.002)	(0.001)	**(0.001)**
$\bar{\theta}_1$	0.866	0.928	0.912	**0.848**
	(0.122)	(0.016)	(0.014)	**(0.016)**
$\bar{\theta}_2$	-0.734	-0.780	-0.790	$\mathbf{-0.718}$
	(0.091)	(0.032)	(0.023)	**(0.020)**

Notes: See Table 1.

Table 5 as well as Figures B.13 to B.15 in Appendix B show the results for this specification. Both depictions cast doubt on the existence of a functional relationship between the exchange rate regime classification and the speed of adjustment and long-run parameters in the exchange rate equation. The optimal degree of homogeneity turns out to be one for both types of coefficients, implying that these coefficients do not depend on the regime classification. Based on the graphs, the only category providing weak evidence in favor of adjustment towards a plausible equilibrium is the one classified as “flexible” exchange rates. Note that these results persist even under a nominal specification not imposing any ordering structure on the classification codes.

5 Conclusion

We proposed and applied a semi-parametric approach to dynamic panel data modelling. Our approach is suitable for models especially in a cross-country environment, where the number of time periods is large enough to enable country-specific estimation of the (parametric part of the) model, but efficiency gains could be achieved by a certain amount of pooling. The non-parametric element is introduced for that purpose, using a local estimation approach with bandwidth which can be set to any value between zero and one to cover all degrees of parameter homogeneity. The application to issue of cross-country homogeneity emerged as special case of a model for categorical conditioning information.

The proposed method generalizes existing approaches to model cross-sectional homogeneity in heterogeneous panels. It allows for partial influence of other countries on estimated coefficients, differentiating between short-run and long-run homogeneity. We applied the method to the case of equilibrium exchange rate modelling, investigating both the speed of adjustment to equilibrium and the long-run exchange rate elasticities. In the first step, we modelled both types of parameters as independent functions of the degree of cross-country homogeneity, finding evidence of largely heterogeneous adjustment and more homogeneous long-run coefficients. In the second step, we also investigated another dimension of homogeneity different from the cross section, and used exchange rate classification data as an ordinal indicator determining coefficient variation. We found that this variable is not able to explain cross-country heterogeneity in the coefficients as the corresponding function is found to be independent of the actual exchange rate regime.

These results were obtained by determination of the optimal value of single parameter λ via cross-validation methods. We argued that this parameter can be interpreted as indicating the degree of homogeneity along the specified dimension, e.g. the cross-section dimension, or other categorical information.

Implications from an optimal degree of homogeneity between zero and one could be twofold: within the suggested non-parametric approach, such a value indicates the specification to be used for most efficient estimation. However, also for standard parametric analyses, this degree can be used to shape groups of countries that are more closely related than others and enable “conventional” pooling.

Appendices

A Local Least Squares Kernel Estimation

Consider the following simple panel model,

$$y_{it} = \boldsymbol{\varphi}(z_{it})'\boldsymbol{x}_{it} + u_{it}, \tag{A.1}$$

where u_{it} denotes a shock with mean zero and variance σ_i^2, uncorrelated across i and t, and $\boldsymbol{\varphi}(z_{it})$ denotes a vector of coefficients linearly combining the regressors within the vector $\boldsymbol{x}_{it}$, conditional on the value z_{it} which is observed for all i and t. The model is estimated by minimizing the following modified residual sum of squares:

$$\hat{\boldsymbol{\varphi}}(z, \lambda) = \underset{\boldsymbol{\varphi}}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} u_{it}^2 \; \kappa(z_{it}|z, \lambda), \tag{A.2}$$

where $\kappa(z_{it}|z, \lambda)$ represents the kernel that determines to what extent an observation (i, t) with nonzero distance $z_{it} - z$ will be included in the estimation for a given value of z and λ. According to Kumar and Ullah (2000), Equation (A.2) can be solved using the local least-squares kernel (LLSK) estimator,

$$\hat{\boldsymbol{\varphi}}(z, \lambda) = [\boldsymbol{\Xi}'\boldsymbol{\Omega}^{-1}(z, \lambda)\boldsymbol{\Xi}]^{-1}\boldsymbol{\Xi}'\boldsymbol{\Omega}^{-1}(z, \lambda)\boldsymbol{\Upsilon}, \tag{A.3}$$

where $\boldsymbol{\Upsilon}$ and $\boldsymbol{\Xi}$ denote the vector and matrix containing dependent and explanatory variables, respectively, in stacked form. In particular, $\boldsymbol{\Upsilon} = (\boldsymbol{\Upsilon}_1{}' \ \boldsymbol{\Upsilon}_2{}' \ \ldots \ \boldsymbol{\Upsilon}_N{}')'$ with $\boldsymbol{\Upsilon}_i = (y_{i1} \ y_{i2} \ \ldots \ y_{iT})'$, $i = 1, 2, ..., N$, and $\boldsymbol{\Xi} = (\boldsymbol{\Xi}_1{}' \ \boldsymbol{\Xi}_2{}' \ \ldots \ \boldsymbol{\Xi}_N{}')'$ with $\boldsymbol{\Xi}_i = (\boldsymbol{x}_{i1}' \ \boldsymbol{x}_{i2}' \ \ldots \ \boldsymbol{x}_{iT}')'$, $i = 1, 2, ..., N$. Furthermore,

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

where $\boldsymbol{K}(z, \lambda)$ is a diagonal matrix containing the values of $\kappa(z_{it}|z, \lambda)$ for $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$:

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

$$\boldsymbol{K}(\boldsymbol{z}_{i,-1}|z, \lambda) = \operatorname{diag}\left(\kappa(z_{i0}|z, \lambda), \, \kappa(z_{i1}|z, \lambda), \, \ldots, \, \kappa(z_{i,T-1}|z, \lambda)\right).$$

Due to cross-section independence of errors, the variance matrix $\boldsymbol{\Omega}$ is given by

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

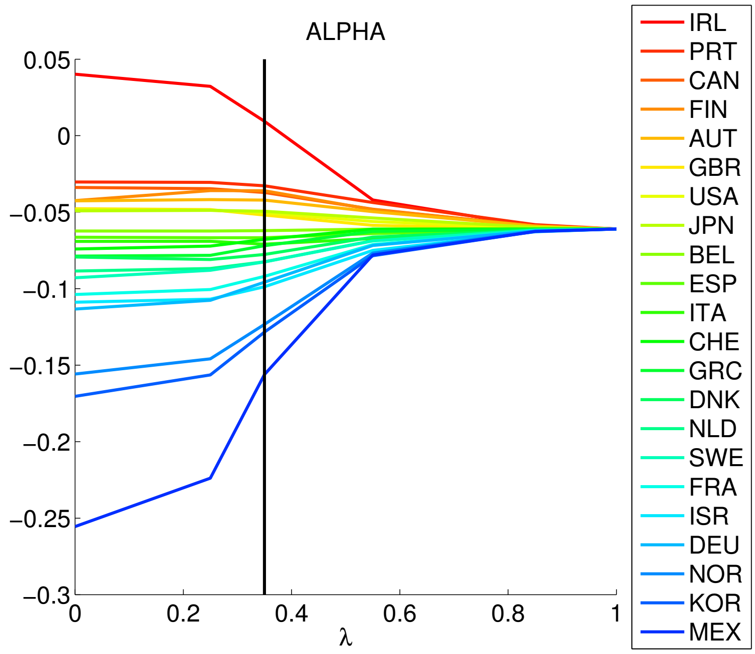
The variance of the parameter estimates can be obtained according to Kumar and Ullah (2000) as

$$V[\hat{\boldsymbol{\varphi}}(z, \lambda)] = [\boldsymbol{\Xi}'\boldsymbol{\Omega}^{-1}(z, \lambda)\boldsymbol{\Xi}]^{-1}\boldsymbol{\Xi}'\boldsymbol{\Omega}_1^{-1}(z, \lambda)\boldsymbol{\Xi}[\boldsymbol{\Xi}'\boldsymbol{\Omega}^{-1}(z, \lambda)\boldsymbol{\Xi}]^{-1}, \tag{A.4}$$

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

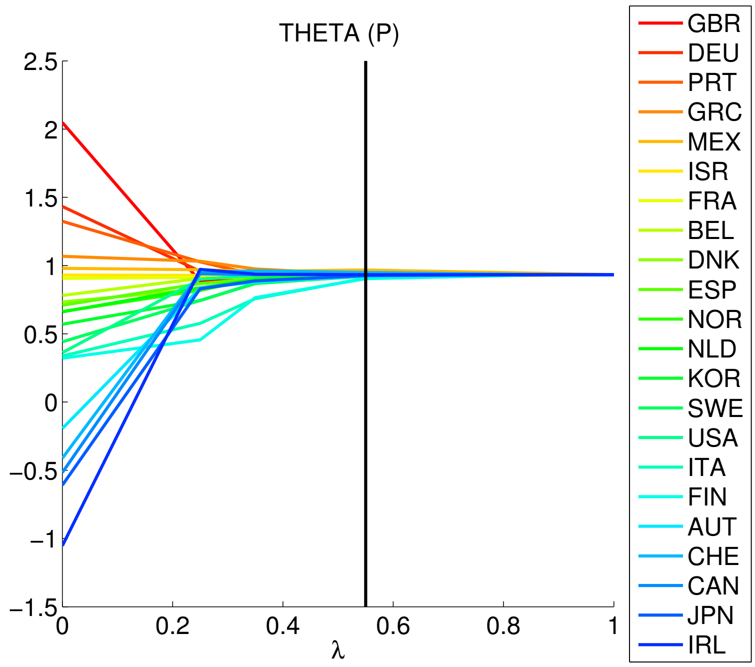
B Figures

Figure B.1: Speed of Adjustment, 22 OECD Countries, 1970–2012



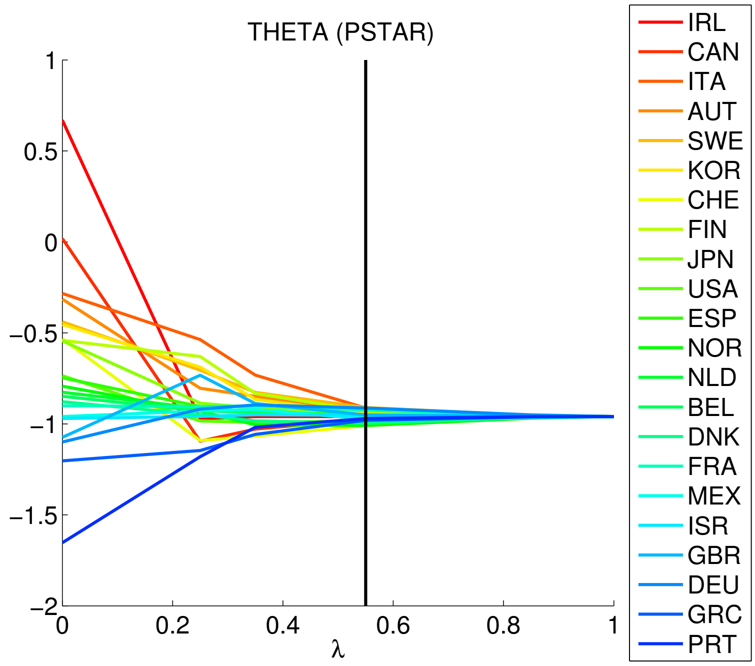
Notes: Coefficients are evaluated at $\lambda \in \{0, 0.25, 0.35, 0.55, 0.85, 1\}$. The vertical line indicates the optimal value for λ corresponding to this coefficient according to cross-validation.

Figure B.2: Long-Run Elasticity to Domestic Prices, 22 OECD Countries, 1970–2012



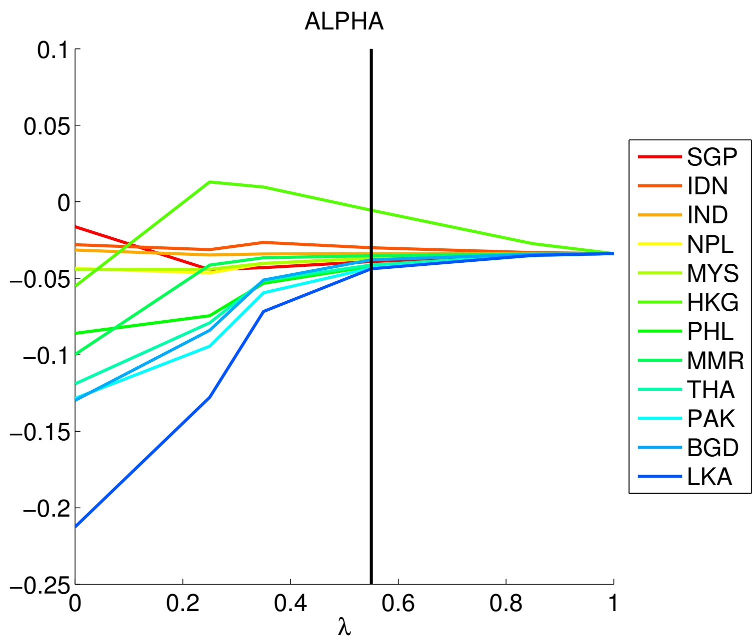
Notes: See Figure B.1.

Figure B.3: Long-Run Elasticity to Foreign Prices, 22 OECD Countries, 1970–2012



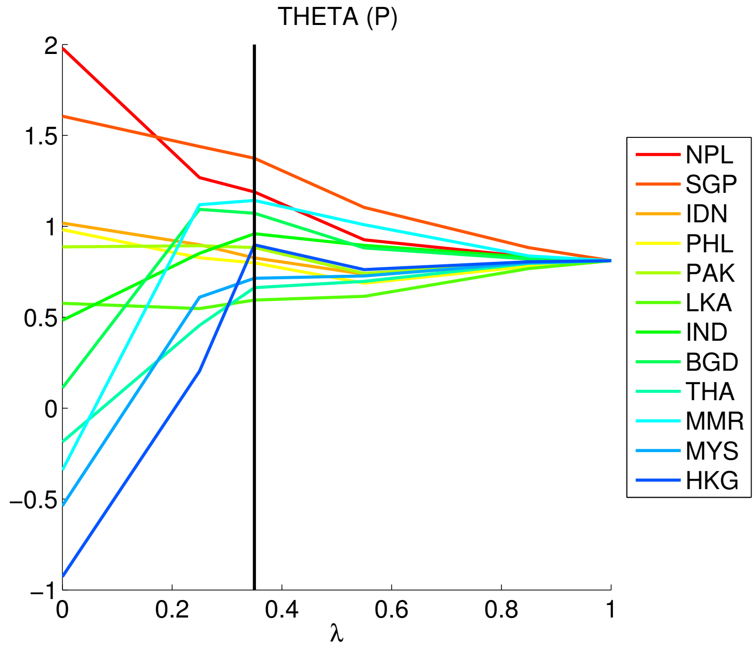
Notes: See Figure B.1.

Figure B.4: Speed of Adjustment, 12 East Asian Countries, 1970–2012



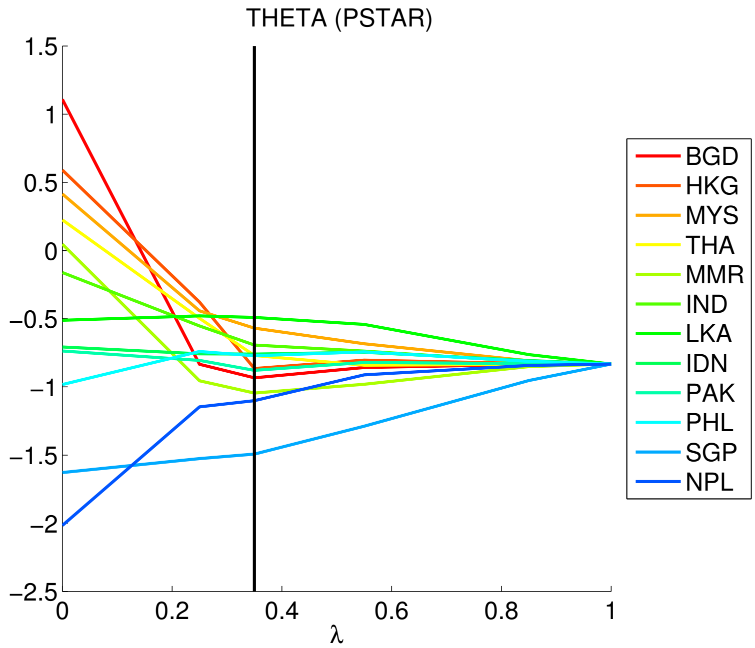
Notes: See Figure B.1.

Figure B.5: Long-Run Elasticity to Domestic Prices, 12 East Asian Countries, 1970–2012



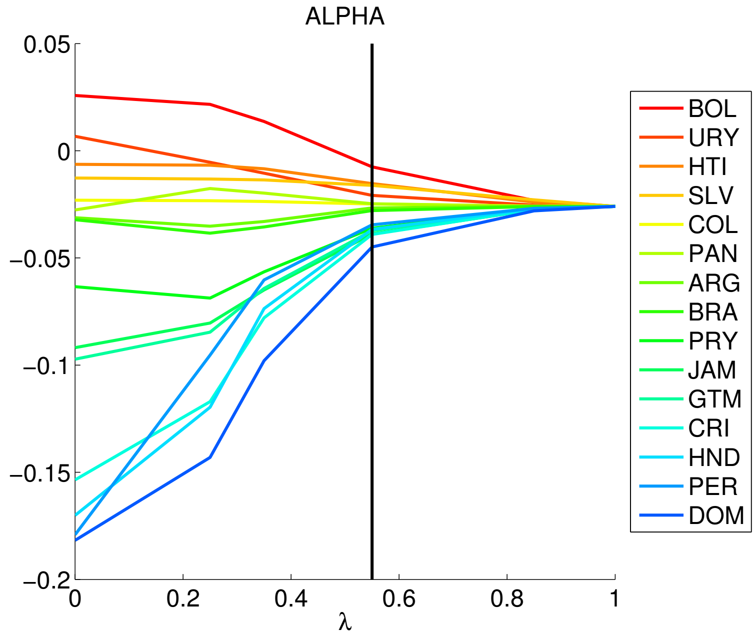
Notes: See Figure B.1.

Figure B.6: Long-Run Elasticity to Foreign Prices, 12 East Asian Countries, 1970–2012



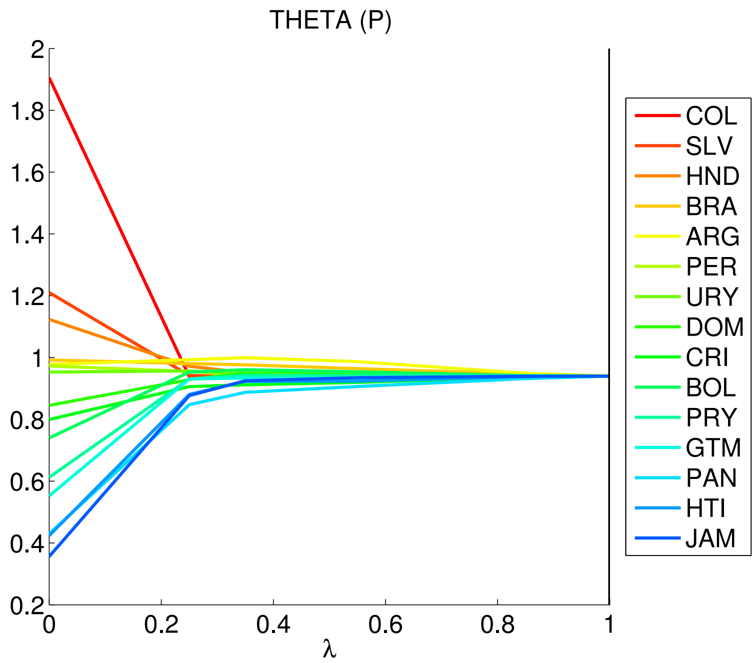
Notes: See Figure B.1.

Figure B.7: Speed of Adjustment, 15 South American Countries, 1970–2012



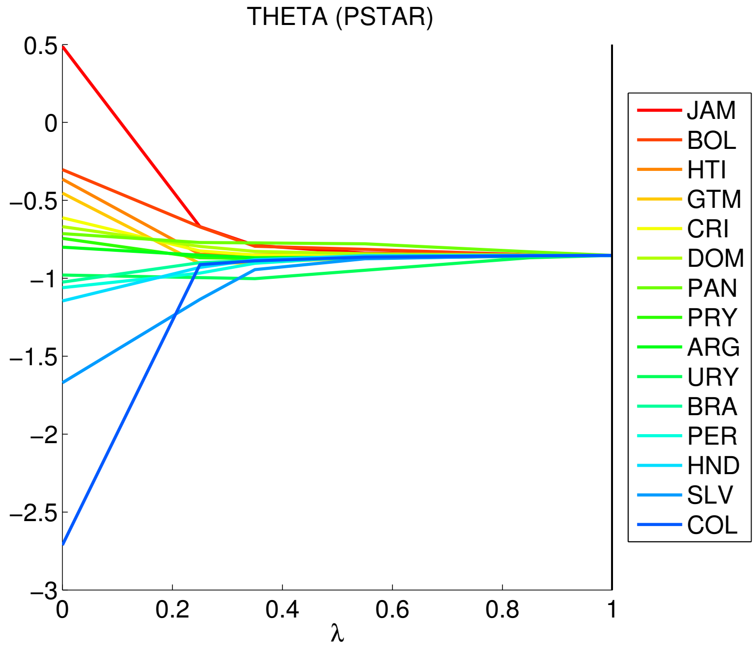
Notes: See Figure B.1.

Figure B.8: Long-Run Elasticity to Domestic Prices, 15 South American Countries, 1970–2012



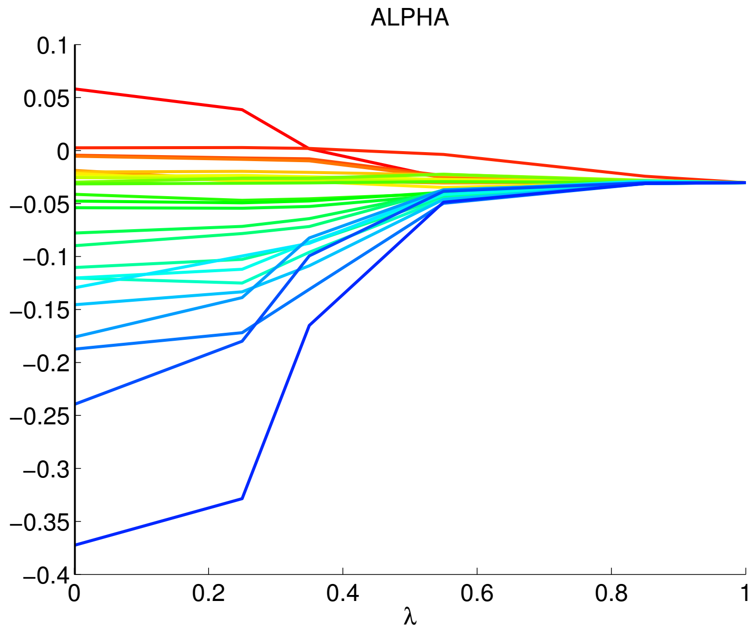
Notes: See Figure B.1.

Figure B.9: Long-Run Elasticity to Foreign Prices, 15 South American Countries, 1970–2012



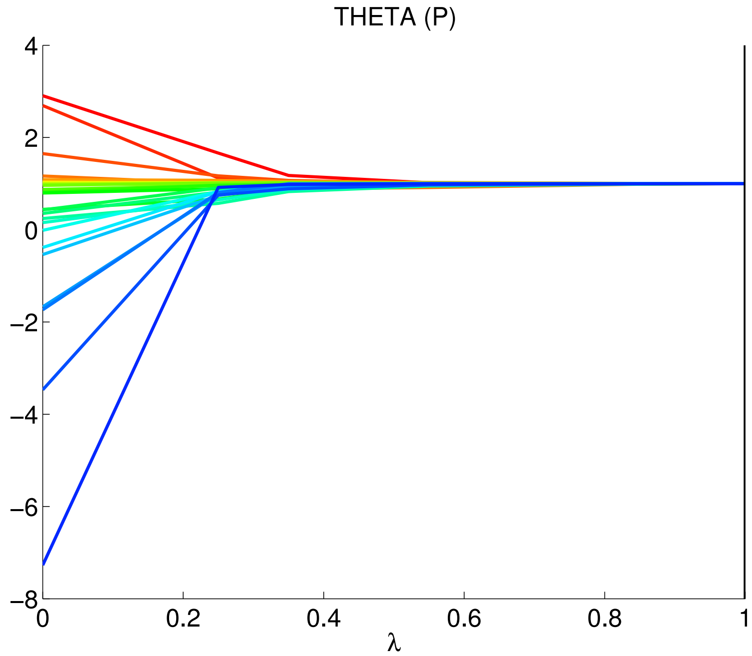
Notes: See Figure B.1.

Figure B.10: Speed of Adjustment, 26 African Countries, 1970–2012



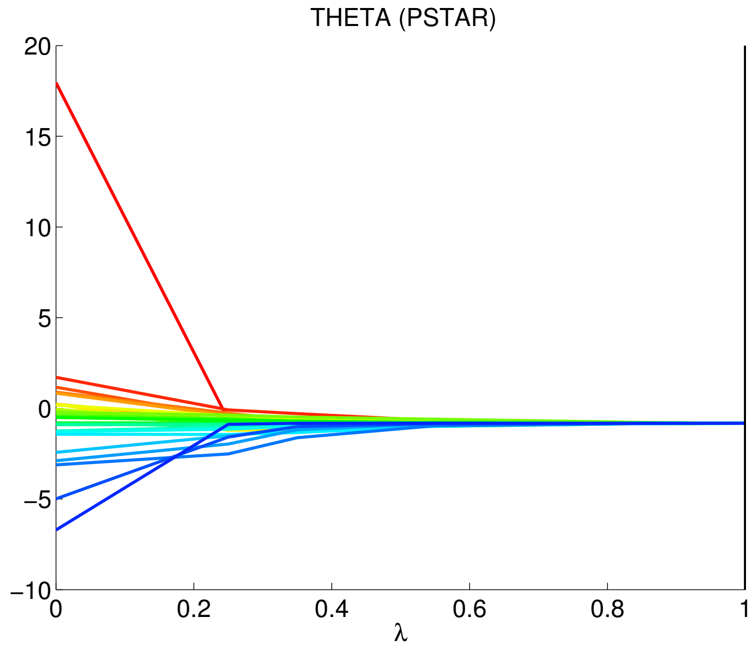
Notes: See Figure B.1.

Figure B.11: Long-Run Elasticity to Domestic Prices, 26 African Countries, 1970–2012



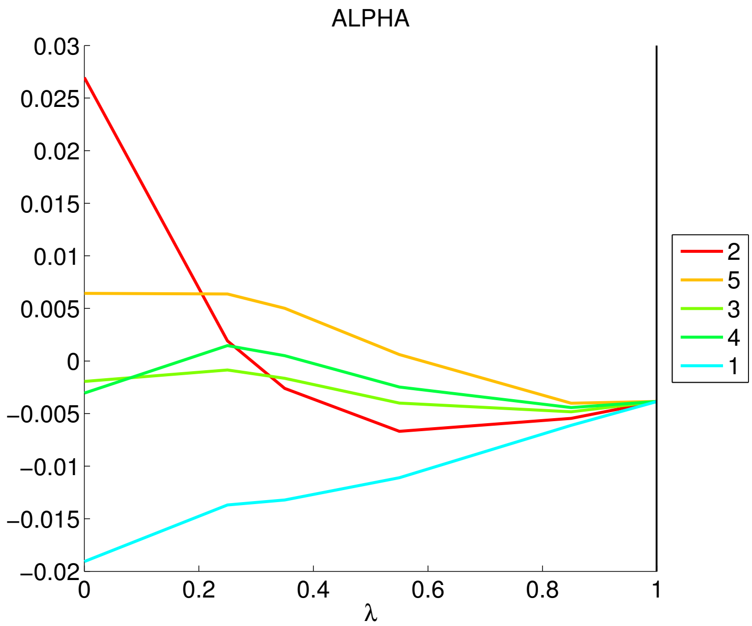
Notes: See Figure B.1.

Figure B.12: Long-Run Elasticity to Foreign Prices, 26 African Countries, 1970–2012



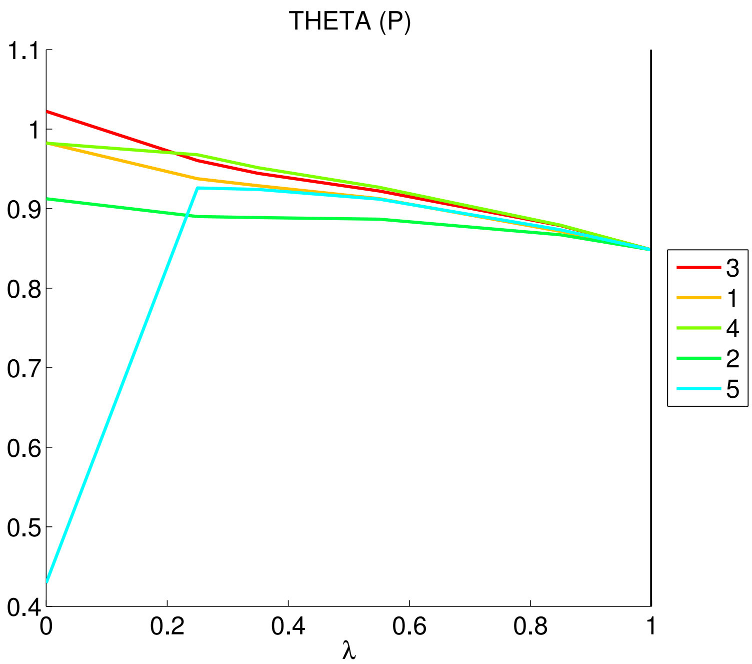
Notes: See Figure B.1.

Figure B.13: Speed of Adjustment, FX Regimes: 66 Countries, 1970–2004



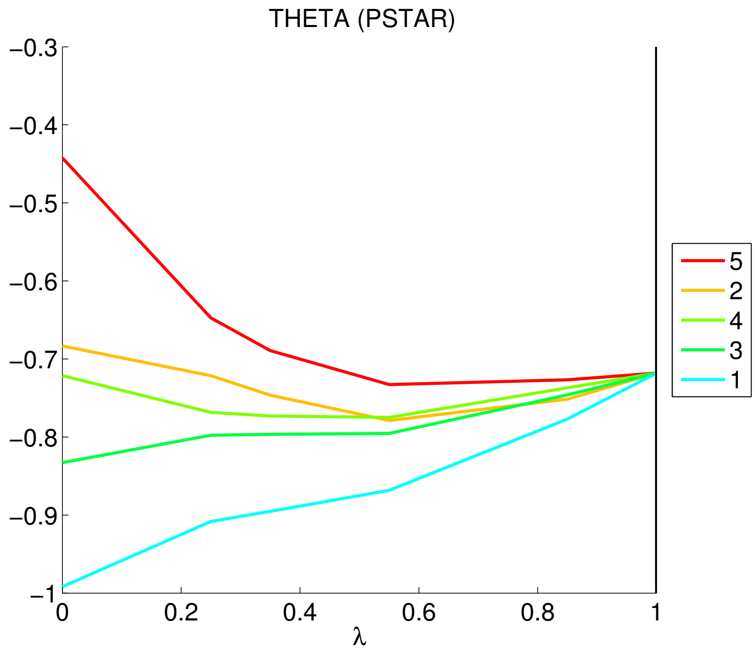
Notes: The sample comprises 66 countries for which exchange rate regime classification data by Levy-Yeyati and Sturzenegger (2005) is available. Original classifications have been recoded as follows: 1 = "flexible", 2 = "dirty float", 3 = "inconclusive", 4 = "crawling peg", 5 = "fixed". Coefficients are evaluated at $\lambda \in \{0, 0.25, 0.35, 0.55, 0.85, 1\}$. The vertical line indicates the optimal value for λ corresponding to this coefficient according to cross-validation.

Figure B.14: Long-Run Elasticity to Domestic Prices, FX Regimes: 66 Countries, 1970–2004



Notes: See Figure B.13.

Figure B.15: Long-Run Elasticity to Foreign Prices, FX Regimes: 66 Countries, 1970–2004



Notes: See Figure B.13.

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