Barbara Chizzolini[**], Bruno Sitzia[*]
Università Luigi Bocconi - Milano

Risk related non linearities in exchange rates:

a comparison of parametric and semiparametric estimates

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ABSTRACT

This paper uses semiparametric techniques to estimate a nonlinear model and compare it to a parametric LSTAR specification of exchange rate determination. In both cases the nonlinearities are modeled as part of the conditional mean of the process, rather than of its variance, thus providing an alternative approach to recent ARCH-type estimations of the same issue. Using a panel data set for five East European countries for years 1993 - 2001, it results that the non parametric data-driven estimates perform a little better but actually support the LSTAR specification. The dependence of current on lagged exchange rates is confirmed to be non linear, with marginal effects that become very significant and negative for abnormal values of the lagged variable. The PPP hypothesis, that is reflected in a ECM component included in the specification, is not rejected by the data.

Keywords: Robinson's Semiparametric estimators, LSTAR, ECM, PPP hypothesis.
JEL code: C14, F31

[**] Corresponding author: Barbara Chizzolini, Università Bocconi, E-Mail:barbara.chizzolini@uni-bocconi.it
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INTRODUCTION

It has been shown in the literature that the process that generates exchange rates contains significant non linearities. Among others, Pagan,Ullah, 1988 and Gallo, 2000 tend to identify the non linearity as a risk component and specify ARCH-type models to test their hypothesis. In a recent paper, Sitzia et al. (2000), propose an alternative LSTAR (Logistic Smooth Transition Auto Regressive)specification to model the existing non linearities in exchange rates series, for five East European Countries currencies against the Euro. The estimated model is actually a combination of an ECM mechanism and an LSTAR component: the lagged level values of the exchange rate and of the price differential that are included in the specification, stand for the equilibrium long run path of exchange rates and price differentials in the assumption that the Purchasing Power Parity (PPP) hypothesis holds. Short run fluctuations in exchange rates are due to changes in the US$ - EURO exchange rate, to inflation differentials between each East European country and the EURO area, and to the LSTAR mechanism that lets differentials in interest rates trigger variations in the current exchange rate only when past changes of the exchange rate itself are “big enough” .

This paper takes Sitzia et al.’s model of exchange rates formation and uses Pagan’s and Ullah’s semiparametric approach to check for and estimate the non linearities in the process. It seems interesting to use for this purpose a non parametric, entirely data-driven, procedure instead of a-priori imposing the LSTAR parametric form, a restriction that might even lead to inconsistent estimates of the parameters of the linear part of the model, in particular of the ECM component.

Section 1 deals with the theory of Semiparametric estimation for panel data and Section 2 presents its empirical application to the model of exchange rates together with the results. In Section 3 the non parametric non linear (NPNL) component will be tested agains the LSTAR mechanism. More in depth analyses of the joint effects on exchange rates of interest spreads and of the lagged values of the endogenous variable as they result from the estimated NPNL component will also be performed.

Conclusions will close the paper.

1. The Theory of Semiparametric Estimation: the case of panel data.

For completeness and presentation purposes it is worthwhile to outline here the theory of semiparametric estimation, when the available data are in panel form. The notation, the description of the estimation procedure and of the properties of the estimators closely follow the paper by Ullah and Roy (1998), who discuss non parametric fixed effect panel estimators. In fact, as in Sitzia et al., our model of exchange rate formation will be estimated on data for five East European countries, using monthly observations from january 1993 through september 2001. Remember also that the model specified in Sitzia et al. may be split into a linear and a nonlinear part, so that it may be written in compact form as:

1]
$$
\begin{aligned}
& y_{it} = \alpha_i + x_{it}'\beta + g(z_{ti}) + u_{it} \qquad i = 1,..,n; t = 1,..,T \\
& E(u_{it} \mid x_{it}) = E(u_{it} \mid z_i) = 0 \\
& u_{it} \rightarrow iid(0, \sigma^2)
\end{aligned}
$$

where x_{it} and z_{it} are a px1 and a dx1 vectors of explanatory variables respectively, and g(.) is the unknown nonlinear function within the model.

Using Robinson's procedure, (see Pagan and Ullah, 1999, chapter 5, Ullah and Roy 1998, p.592), take the conditional expectation of equation 1.1 with respect to z and obtain:

[2] $$E(y_{it} \mid z_{it}) = \alpha_i + E(x_{it} \mid z_{it})'\beta + g(z_{it}) + E(u_{it} \mid z_{it}) = \alpha_i + m_x(z_{it}) + g(z_{it})$$

Subtract 2 from 1.1:

[3] $$y_{it}^* = y_{it} - E(y_{it} \mid z_{it}) = (x_{it} - m_x(z_{it}))'\beta + u_{it} = x_{it}^{*\prime}\beta + u_{it}$$

3 is a linear equation in the transformed variables y_{it}* and x_{it}*, that can be estimated with OLS (no fixed effects) to get consistent estimates, b, of β, the parameters in the linear part of the model. The next step consists in estimating the nonlinear function $g(z)$ in the regression:

[4] $$y_{it}^{**} = y_{it} - x_{it}'b = \alpha_i + g(z_{it}) + u_{it}$$

1.1 The Local Linear Kernel Estimator

The suggestion in the nonparametric literature, in particular in Ullah and Roy 1998, is to perform pooled local linear Kernel (nonparametric) regressions to estimate a_i+$g(z_{it})$ as well as the conditional means $E(y_{it}|z_{it})$ and $E(x_{it}|z_{it})$ in equation 3. Setting for a moment aside the estimation of the a_i, consider the nonlinear function

[5] $$y_{it} = m(z_{it}) + u_{it}$$

and its linear approximation through a Taylor series expansion around z:

$$y_{it} = m(z) + (z_{it} - z)' \left.\frac{\partial m(z)}{\partial z}\right|_z + v_{it} = m(z) + (z_{it} - z)'\delta(z) + v_{it}$$

or

[6] $$y = X(z)\theta(z) + v$$

where

$X(z) = \text{nTx(d+1)}$ matrix, with ith element $[1 \;\; \text{z}_{\text{it}} - z]$

$\theta(z) = [m(z) \quad \delta'(z)]' = (d+1)x1$ parameter vector

Then, apply Weighted Least Squares to 6 to get to an estimate of $\theta(z)$, namely:

$$\min_{\theta(z)} v'Kv \rightarrow \tilde{\theta}(z) = (X'(z)K(z)X(z))^{-1} X'(z)K(z)y$$

[7] *where*

$K = K((z_{it} - z)/h)$ is the Kernel or weight function

Note that through this procedure, you jointly estimate the mean, $m(z)$, and the gradient, $\delta(z)$, of the conditional expectation function in the neighborhood of z. That is, for a neighborhood of width h around each value of z, you fit a regression line with constant $m(z)$ and slope $\delta(z)$, that can be interpreted as the values of the nonlinear function computed at z and of the response parameters of y with respect to the regressors, respectively.

It is proved that if the Kernel function satisfies some smoothness conditions, if h goes to zero as n tends to infinity, and if some other conditions on y and z are satisfied, the estimated parameters converge to normality, more precisely (see Ullah and Roy, 1998, p 586),

$$(nh^{d})^{1/2}(\tilde{m}(z)-m(z)) \xrightarrow{n\to\infty} N\left(0, \frac{\sigma_v^2(z)}{Tf(z)}\int K^2(\Psi)d\Psi\right)$$

[8]

$$(nh^{d+2})^{1/2}(\tilde{\delta}(z)-\delta(z)) \xrightarrow{n\to\infty} N\left(0, \frac{\sigma_v^2(z)}{Tf(z)}\frac{\int K^2(\Psi)\Psi^2 d\Psi}{\mu_2^2}\right)$$

This result allows to estimate standard errors for the parameters, and draw inference from the results.

h, the window width, is estimated using the formula: $h_j^{opt} = \psi_j \sigma_j n^{-1/(2l+d)}$, where ψ_j is an unknown constant, σ_j is the variance of z_j, l is the order of the kernel and *d* is the number of variables in the joint density being estimated. N © (J. Racine 2001) performs a data driven estimation of the scale factor, ψ_j, based on the Least Squares Cross Validation "leave-one-out" method described in Pagan and Ullah, 1999, p.119. This procedure minimizes with respect to *h* the mean of the Estimated Prediction Error: $E(EPE(h)) = E\left(n^{-1}\sum(y_i - \tilde{m}(z_i))^2\right)$, where $\tilde{m}(z_i)$ is the estimated regression line or non parametric conditional mean of *y* on *z*. As for the choice of the Kernel function, the second order gaussian kernel, the default in the nonparametric regression program N ©, will be used in estimation, see Racine 1999, (p.67-70). The multivariate kernel that is necessary to estimate the conditional means in 3 and 4, is the product kernel:

$K(Z) = K(z_1)\times K(z_2)\times\cdots\times K(z_d)$

If there exist individual specific fixed effects

[9] $y_{it} = \alpha_i + m(z_{it}) + u_{it}$

and if you use the local linear kernel estimator, that is you linearly expand the function around *z*, α_i becomes a part of the "constant", so that the estimated *m(z)* actually is the sum of the individual fixed effect and of the nonlinear function computed at *z*. Ullah and Roy 1998, p.589, suggest a further transformation of the data that allow to separately estimate the two elements, but it does not seem to be necessary to do so in what follows. It will have to be remembered that the nonlinear functions of *z* that will be presented in the following pages, all implicitly contain the individual specific effects.

One last remark must address the fact that the regressors vector, *z,* contains the endogenous variable, lagged one and two periods. This does not affect the procedure and the results on consistency and asymptotic distribution of the SP estimators hold, as long as the independence between the error terms and *z* is satisfied, i.e., in this case, if the error terms are not serially correlated.

2. The Semiparametric estimation of Model [1]

The procedure outlined above has been used to estimate a Semiparametric alternative to the model specified in Sitzia et al., Model [1] from now on:

Model [1]

$$\Delta \log(e_{it}) = \alpha_i + \beta_1 \left(\Delta \log(P_{it}) - \Delta \log(P_{EU,t})\right) + \beta_2 \Delta \log(e_{US\$/EU,t}) + \beta_3 \log(e_{it-1}) + \beta_4 \log\left({P_{it-1}}/{P_{EU,t-1}} \right) +$$

$$\beta_5 \left(r_{ti} - r_{EU,t}\right) \left[1 - \exp\left(350 * \left(\frac{\Delta \log(e_{it-1}) - \Delta \log(e_{it-2})}{2} \right) - 1.95 \right)^{-1} \right]$$

The variable definitions and some descriptive statistics are in table 1, index *i* identifies the five East European Countries: Hungary, Czeck Republic, Poland, Slovenia and Slovakia, and *t* indexes monthly observations from January 1993 through September 2001. This specification is based on a simplified version of the traditional Flexible Price Monetary Model. It includes an ECM term that models the long run equilibrium path that connects exchange rates and price differentials, and the LSTAR mechanism that models how interest rates differentials affect exchange rates nonlinearly as a function of the volatility of the process, that is as a function of risk.

Table 1 – The list of variables

	SYMBOL	DEFINITION
Y	$Dlog(e_i)$	Rate of change of the exchange rate, by country, against Euro
X1	$Dlog(P_i)-Dlog(P_{EU})$	Inflation differentials
X2	$Dlog(e_{US\$-EU})$	Rate of change of the US$/Euro exchange rate
X3	$log(e_{i,t-1})$	Lagged log level of EaEucoutry£/Euro exchange rate
X4	$log(P_{i,t-1}/(P_{EU,t-1})$	Lagged log price differentials
LSTAR	$\left(r_{ti} - r_{EU,t}\right)\left[1 - \exp\left(350 * \left(\frac{\Delta \ln(e_{it-1}) - \Delta \ln(e_{it-2})}{2}\right) - 1.95\right)^{-1}\right]$	LSTAR component
Z1	$(r_i - r_{EU})$	Interest rate differentials
Z2	$Dlog(e_{i,t-1})$	One period Lagged Endogenous
Z3	$Dlog(e_{i,t-2})$	Two period Lagged Endogenous
MY	E(Y | Z)	NP Conditional mean of Y on Z
MX1	E(X1 | Z)	NP Conditional mean of X1 on Z
MX2	E(X2 | Z)	NP Conditional mean of X2 on Z
MX3	E(X3 | Z)	NP Conditional mean of X3 on Z
MX4	E(X4 | Z)	NP Conditional mean of X4 on Z
NPNL	E((Y-XB)|Z)	Non Parametric Nonlinear component

Notes: *i = CZ, HU, PL, SK, SN; D = first difference operator; log = logarithm*

Table 1 (continue) – Descriptive statistics on the stacked data, common sample (1993:04 – 2001:09)

	Mean	Median	Maximum	Minimum	Std. Dev.	Jarque-Bera	Probability
$Dlog(e_i)$	0.004476	0.003871	0.099671	-0.10868	0.017036	1319.853	0
$Dlog(P_i)$-$Dlog(P_{EU})$	0.005868	0.004062	0.060239	-0.02177	0.008723	1044.696	0
$Dlog(e_{US\$-EU})$	-0.00278	-0.0061	0.052344	-0.04558	0.022748	16.35081	0.000281
$log(e_{i,t-1})$	3.780565	3.673731	5.587743	0.696448	1.475605	48.05749	0
$log(P_{i,t-1}/(P_{EU,t-1})$	0.113943	0.116855	0.625651	-0.54318	0.216842	1.217865	0.543931
$(r_i - r_{EU})$	10.71223	10.3035	52.91	-1.488	7.731825	51.7439	0
LSTAR	5.046543	3.011501	30.44552	-1.38737	5.52697	237.9494	0
MY	0.004676	0.00301	0.087304	-0.02156	0.008026	13644.03	0
MX1	0.005826	0.004689	0.027914	-0.00222	0.004504	148.607	0
MX2	-0.00262	-0.00311	0.045047	-0.03329	0.005363	8586.646	0
MX3	3.663435	3.73147	5.07855	0.860213	0.60998	371.622	0
MX4	0.103941	0.11051	0.366347	-0.30341	0.087832	126.6757	0
NPNL	0.001536	-0.00017	0.086304	-0.02415	0.007364	31505.7	0

Table 2 shows the estimated equation 3, the "first step" OLS estimates for the linear part of model [1] performed on the transformed variables y^* and x^* (in the notation of section 1). From the results obtained with the ECM – LSTAR specification by Sitzia et al., and from the theoretical a-prioris, we want parameters β_1 through β_4 to be significant, and for the PPP hypothesis to be accepted by these data, that the lagged levels of the exchange rates and price differentials be opposite in sign and almost the same in absolute value.

Both changes in price differentials and changes in $e_{US\$-EU}$ are significant and positive . However the two coefficients of the error component variables, the lagged log of exchange rates and price differentials, are significant only at the 10% level. The negative sign of the coefficient attached to the lagged level price differentials and the little significance of the whole ECM component do not fully support at this stage the PPP hypothesis.

Table 2 – estimated equation [3]

Dependent Variable: $Dlog(e_i)$-MY
Method: GLS (Cross Section Weights)
Date: 01/31/02 Time: 18:27
Sample: 1993:04 2001:08
Included observations: 101
Balanced sample
Total panel observations 505
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	t-Statistic	Prob.
$Dlog(P_i)$-$Dlog(P_{EU})$-MX1	0.173196	2.452425	0.0145
$Dlog(e_{US\$-EU})$-MX2	0.129202	4.924747	0.0000
$log(e_{i,t-1})$-MX3	0.000780	1.748454	0.0810
$log(P_{i,t-1}/(P_{EU,t-1})$-MX4	-0.005112	-1.695803	0.0905

R-squared	0.077639	Log likelihood	1765.861
Adjusted R-squared	0.072116	Sum squared r.	0.088862

The next step in the SemiParametric analysis of Model [1] consists in computing, using the estimated coefficients in table 2, the new transformed endogenous variable, y^{**} (see [4]), and in performing the final non parametric regression of y^{**} on the variables in z, (see [9]). The estimated Non Parametric conditional mean of y** on z is going to be called from now on NPNL. As a last step we are going to reestimate the full model of exchange rates using as a regressor NPNL instead of the LSTAR mechanism.

Table 3 presents the pooled fixed effect estimates of model [1] in the LSTAR version and in its SP counterpart. The estimates and the goodness of fit of the two specifications are going to be compared and commented. In particular the two alternative nonlinear components are going to be analysed to test whether the nonparametric estimates support or reject the LSTAR functional form. In the following section, the paper will address the question of how and how significantly the interest rates spreads and the lagged values of the endogenous variable affect NPNL hence the changes in exchange rates.

3. A comparison between the LSTAR and the NPNL estimates

How do the semiparametric estimates compare with the LSTAR model? Or in other words how is it posible to check if the imposed parametric LSTAR mechanism is supported by the data? The nonparametric test T suggested by Ullah (1985), is a preliminary simple specification test that can easily be computed on our data, where the hypothesis we wish to test is:

[10] $$\begin{aligned} &H_0 : E(y \mid Z) = g(Z, \delta) = LSTAR \\ &H_1 : E(y \mid Z) = m(Z) \end{aligned}$$

[11] $$T = \frac{(RSS^{P} - RSS^{NP})}{RSS^{NP}} = \frac{\sum u_{t,P}^2 - \sum u_{t,NP}^2}{\sum u_{t,NP}^2}$$

If T is large, H_0 is rejected. It can be proved that under some normalizing transformations T is asymptotically normally distributed (see Lee-Ullah, 2000, p.6). The residual sums of squares in the formula are computed using the residuals of the FEGLS estimations of model 1, where the nonlinear component is either the LSTAR or the estimated non parametric function

Table 3 shows the estimated regressions as well as the computed T test for the LSTAR model against the SemiParametric model. The number is shown in absolute value with no associated P value of the test because our sample dimension is far from asymptotic and it cannot be hoped that the T test be normally distributed. The computed values however show that the SP model performs better than the LSTAR model by approximately 25% which does not seem to be an irrelevant fraction of explanatory power.

However, the SP estimates reproduce in terms of significativity and absolute value of the coefficients the results obtained by Sitzia et al., namely the long run equilibrium path between exchange rates and price differentials seems to be accepted by this specification. Moreover the Non Parametric Non Linear component enters as significantly as the LSTAR mechanism in the estimated regression. (The coefficients associated to the two terms are different in signs and absolute values because of how the two term were constructed. LSTAR is a nonlinear combination of the variables involved (*z1,z2,z3*) that approximately keeps the location of the interest rate differentials. NPNL is the conditional mean of *y*** (*Dlog(e)-X'b*), substantially an error term with location close to that of *Dlog(e)*, the dependent variable. See the descriptive statistics in table 1 above).

Table 3. A comparison between the LSTAR and the NonParametric functions

Dependent Variable: $Dlog(e_i)$
Method: GLS (Cross Section Weights)
Sample: 1993:04 2001:08
Included observations: 101
Number of cross-sections used: 5
Total panel (balanced) observations: 505
White Heteroskedasticity-Consistent Standard Errors & Covariance

	Nonlinear = NPNL		Nonlinear = LSTAR	
Variable	Coefficient	P value	Coefficient	P value
$Dlog(P_i)$-$Dlog(P_{EU})$	0.138431	0.0405	0.301936	0.0003
$Dlog(e_{US\$-EU})$	0.124967	0.0000	0.146030	0.0000
$log(e_{i,t-1})$	-0.032770	0.0092	-0.042266	0.0014
$log(P_{i,t-1}/(P_{EU,t-1})$	0.020347	0.0743	0.022556	0.0548
Nonlinear Comp.	1.150099	0.0000	-0.000557	0.0000
Fixed Effects				
HU--C	0.171401		0.226251	
PL--C	0.037450		0.056717	
CZ--C	0.116858		0.150846	
SN--C	0.171416		0.223508	
SK--C	0.122422		0.159066	
R-squared	0.373369		0.215566	
SSR	0.087526		0.110061	
T	**0.2574**			

To reach further insight on how differently the LSTAR and nonparametric nonlinear (NPNL) mechanism behave in time and by country see figure 2.

For all countries, it is evident how NPNL incorporates some individual and maybe time specific elements (the α_i in equation 9) that the LSTAR mechanism does not. Taking this into account, the two series do not differ too much in term of turning points, but rather in amplitude of the variation they record. The differences are more striking in Poland and Slovakia: in the former country NPNL shows only one relevant peak at the beginning of 1999. Viceversa, in the latter country it is LSTAR that has a smoother behavior.

It is maybe more important at this stage to check whether and how much the individual conditioning variables z_1, z_2, z_3 affect NPNL and, indirectly, *Dlog(e)*. Figure 3 shows the partial derivatives of NPNL with respect to $z_1, z_2,$ and z_3, the interest rate differential, and the lagged one and two periods *Dlog(e)* respectively, for Hungary and Slovakia. Although not shown, the pattern of the estimated parameters is similar for the other three countries.

The estimated $\delta(z_1)$ (see [6] above), are never significantly different from 0, and so are the $\delta(z_3)$ parameters: neither the interest rate differentials nor the twice lagged endogenous variable seem to affect NPNL and indirectly exchange rates. The marginal effect of z_2, the endogenous variable lagged once, instead, strongly depends on the value taken on by z_2 itself: for very large or very small past changes in exchange rates, current exchange rates react strongly and in the opposite direction. No significant inertial effect exists for values of $\mathrm{dlog}(e_{t-1})$ close to 0.

Figure 2 – LSTAR vs NPNL (normalized data)

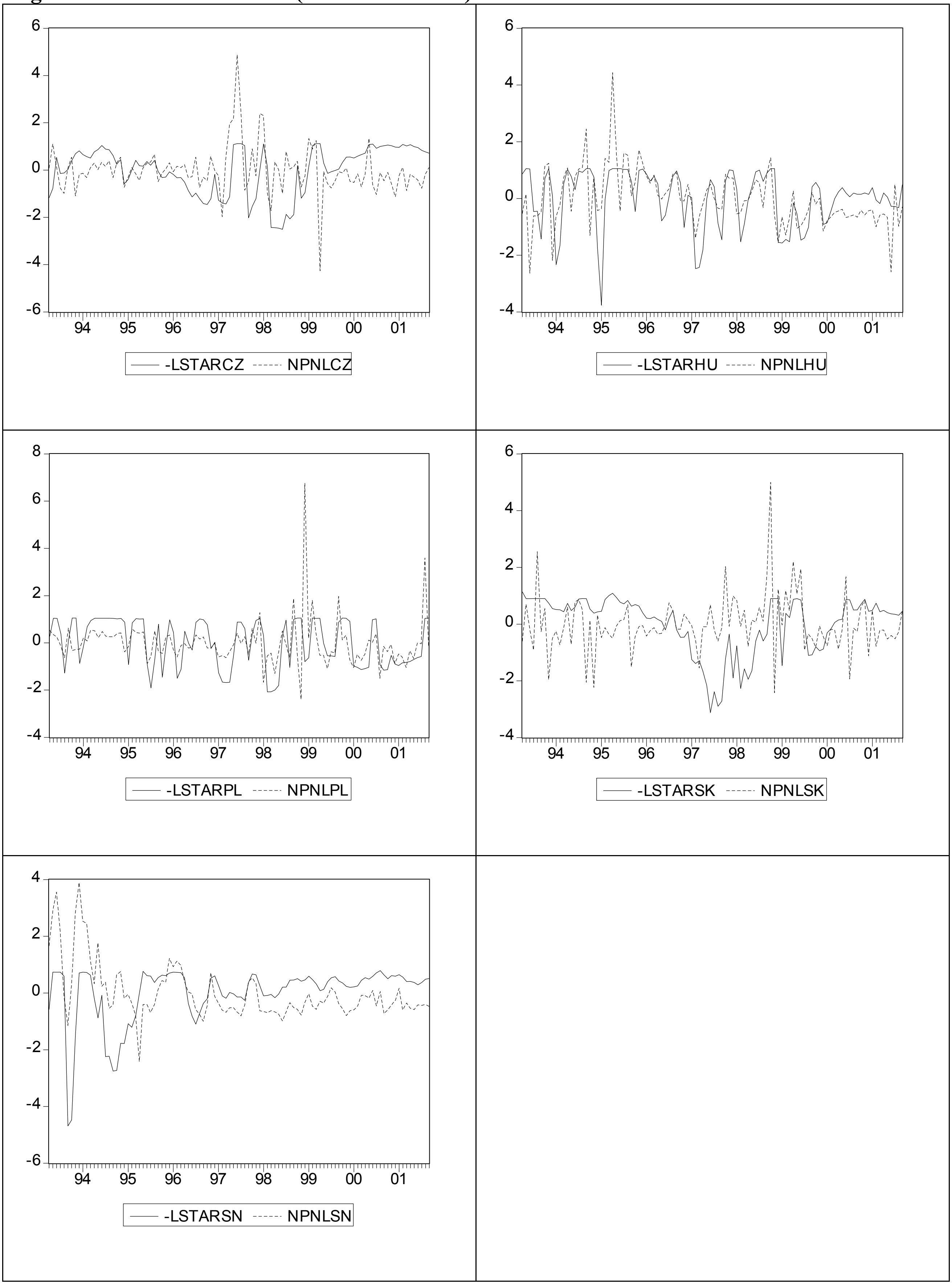
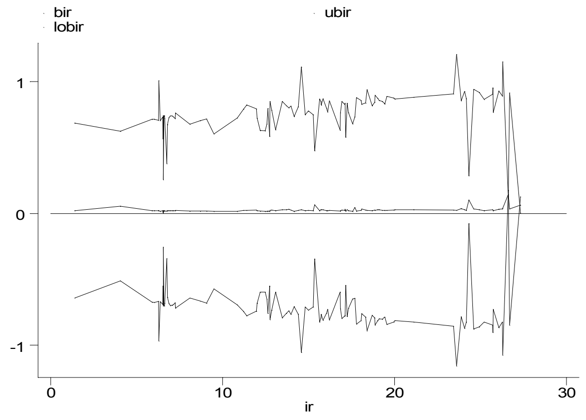
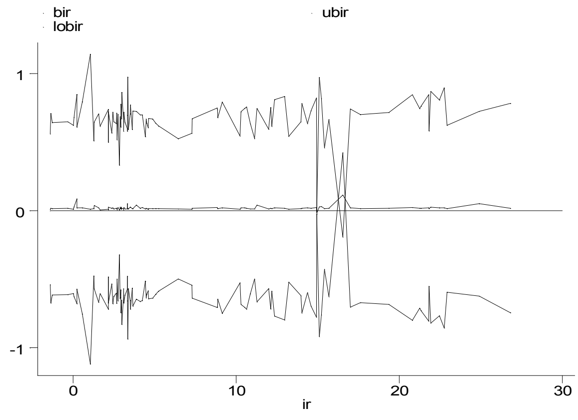


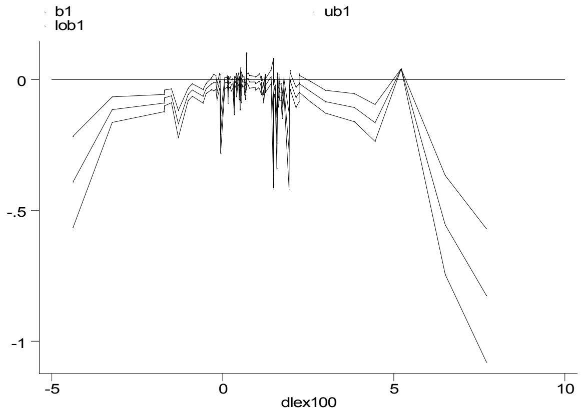
Figure 3. The estimated parameters



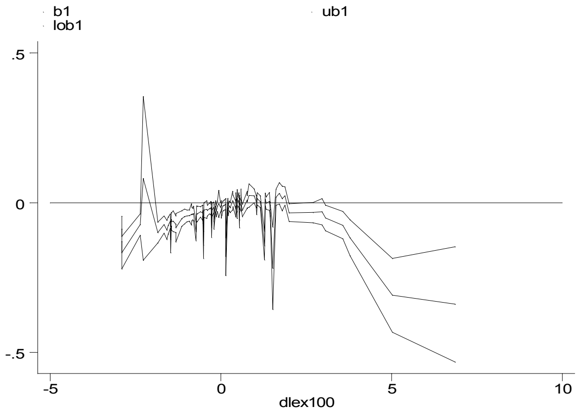
Hungary: d(NPNL)/d(IRHU-IREU)



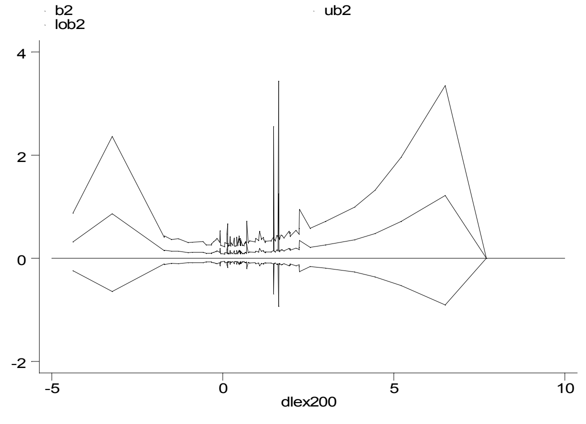
Slovakia: d(NPNL)/d(IRSK-IREU)



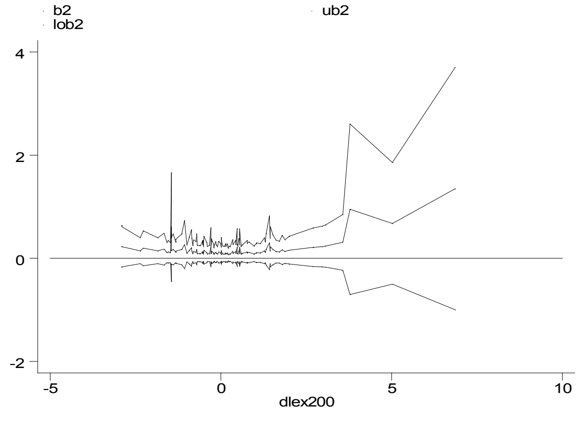
Hungary: d(NPNL)/d(DLOG(EXHU(-1)))



Slovakia: d(NPNL)/d(DLOG(EXSK(-1)))



Hungary: d(NPNL)/d(DLOG(EXHU(-2)))



Slovakia: d(NPNL)/d(DLOG(EXSK(-2)))

From this first look at the estimated effects of the variables in the nonlinear mechanism, it looks as if only the lagged one period endogenous variable is relevant in explaining current changes in exchange rates, conditional on the variations in the X variables.

Summarizing, the evidence suggests that the data support the LSTAR specification: it is able to capture the turning points and the periods of "abnormal fluctuations " in the exchange rates series almost as well as its nonparametric unrestricted counterpart. However not all the variables introduced in the nonlinear component of model [1] seem to be relevant in explaining exchange rates, and the test T, above, gives some indication of mispecification of LSTAR as the functional form that links the endogenous variable, exchange rates, to interest rate differentials and its own lagged values. Would a different parametric functional form approximate NPNL better than LSTAR?

It results that a quadratic expression of the Z variables (Table 4) replicates NPNL quite well. In particular it results that the linear term of the economically relevant interest rates differential variable becomes statistically significant in this regression if more recent observations are added to the sample. So is its cross with the Z_3 (DLOG(EX(-2))) term. This leads to presume that today's changes in exchange rates do depend on past volatility and that, in turn, variations in interest spreads trigger a response in current exchange rates only if coupled with lagged exchange rates variations. This result actually confirms the logic underlying the LSTAR mechanism.

Table 4 – A quadratic approximation to the NPNL function.

White Heteroskedasticity-Consistent Standard Errors & Covariance
Dependent Variable: NPNL?
Method: GLS (Cross Section Weights)

	Sample: 1994:01 2000:01 Included observations: 73 Balanced sample Total panel observations 365		Sample: 1993:04 2001:09 Included observations: 102 Balanced sample Total panel observations 510	
Variable	Coefficient	Prob.	Coefficient	Prob.
Z1?	0.000181	0.0550	0.000210	0.0000
Z2?	0.193647	0.0009	0.156628	0.0000
Z3?	-0.051263	0.3808	-0.086412	0.0001
Z1?^2	7.47E-07	0.8707	-9.03E-07	0.4027
Z2?^2	2.614808	0.4777	1.381328	0.6009
Z3?^2	-2.498541	0.0813	-1.867689	0.0291
Z1?*Z2?	0.000816	0.9372	0.005774	0.1933
Z1?*Z3?	0.007408	0.2081	0.006630	0.0121
Z2?*Z3?	-1.723849	0.3007	-1.212936	0.4348
Fixed Effects				
HU--C	-0.001782		-0.001946	
PL--C	-0.000192		0.000178	
CZ--C	-0.002229		-0.002235	
SN--C	-0.001736		-0.001506	
SK--C	-0.002704		-0.002458	
Adjusted R^2	0.662682		0.699502	

4. Conclusions

The dynamic processes that generate exchange rates have a relevant component that cannot be modeled as a linear combination of some explanatory variables. Theory usually refers to this component as "risk" or "risk premium". Econometric specifications of exchange rate models have hence lately been of the ARCH-GARCH type, that is models where the variance of the process (a proxy of risk) is estimated together with its mean. An alternative parametric specification would include a nonlinear function of some explanatory variables in the mean of the process. In particular a LSTAR-type specification has recently been proposed by Sitzia and Brasili, where current exchange rates, among other things, react to interest rates differentials only in normal times, that is if there were no significant devaluations.

It is however well known that functional mispecifications in a regression may lead to inconsistent estimates of all parameters in the equation, and recent applied literature has started using NonParametric techniques to estimate the risk component in exchange rate models, again in a way that is strongly similar to ARCH-type settings. In other words, the non parametric procedures are used to estimate a (non linear in this case) autoregressive function for the variance of the process under analysis.

This paper uses the same kind of techniques, suggested first by Robinson and then by Pagan, Ullah and Roy in a series of articles, to estimate the semiparametric counterpart of the LSTAR model above, where nonlinearities in exchange rates determination are a part of the conditional mean of the process, rather than of its variance.

It results that the non parametric data-driven estimates perform a little better but actually support the LSTAR specification. In particular the dependence of current on lagged exchange rates is confirmed to be highly non linear, with marginal effects that become very significant and negative for high or low values of the lagged variable. Interest rates differentials certainly do not affect current exchange rates in a linear form. There is some indication however that their cross effect together with lagged exchange rates is significant.

The last result is that the linear part of the parametric LSTAR model is also supported by the Semi Parametric estimates: there is no indication of bias in the estimated parameters due to functional mispecification. In particular the PPP hypothesis, that is reflected in the ECM component included in the specification, is not rejected by the data.

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