8. DETERMINANTS OF THE DINAR-EURO NOMINAL EXCHANGE RATE[1]

Milan NEDELJKOVIĆ[2]
Branko UROŠEVIĆ[3]

Abstract

This paper studies the drivers of the daily dynamics of the nominal dinar-euro exchange rate from September 2006 to June 2010. Using a novel semiparametric approach we are able to incorporate the evidence of nonlinearities under very weak assumptions on the underlying data generating process. We identify several factors influencing daily exchange rate returns whose importance varies over time. In the period preceding the financial crisis, information in past returns, changes in households' foreign currency savings and banks' net purchases of foreign currency are the most significant factors. From September 2008 onwards other factors related to changes in country's risk and the information processing in the market gain importance. NBS interventions are found to be effective with a time delay.

Keywords: foreign exchange market; partially linear model; splines; kernel; Serbia

JEL Classification: F31, C14, G18

I. Introduction

Over the past three decades empirical literature documented that traditional macro fundamentals perform poorly in explaining the short-run movements in the floating exchange rates[4]. The recent microstructure literature, pioneered by a series of papers

---

[1] We would like to thank Shujie Ma for sharing her code on the spline backfitted kernel estimator of the partially linear model. We also thank anonymous referees, Bojan Markovic, Bosko Zivkovic, Milan Aleksic, Mirko Djukic, Ana Ivkovic, Marina Komatina-Mladenovic and Mirjana Palic for useful comments. The views expressed in the paper are those of the authors and do not necessarily represent the official view of the National Bank of Serbia.

[2] National Bank of Serbia, Belgrade and .Faculty of Economics, Finance and Administration, Singidunum University, Belgrade, Serbia.

[3]. Faculty of Economics, University of Belgrade and National Bank of Serbia, E-mail: branko.urosevic@nbs.rs. Branko Urošević gratefully acknowledges financial support of the Serbian Ministry of Science and Technological Development, Grant No OH 179005.

[4] For recent surveys see for example Sarno and Taylor (2003) and Cheung, *et al*. (2005).

by Lyons (1995, 2001) and Evans and Lyons (2002, 2008), has provided a promising alternative by establishing a close link between daily exchange rate movements and order flow. The latter literature essentially models the exchange rate as the price equating supply and demand on the foreign exchange (FX) market and focuses on the details of the currency trading between different market participants without including any form of direct macro influences on the exchange rate. Recently, Evans (2010) proposed a hybrid model of the exchange rate dynamics which in addition to the key features of the microstructure literature explicitly includes the interest rate dynamics into the price-setting process of the FX agents, in line with the fact that central banks today use short-term interest rates rather than monetary aggregates as a policy instrument. The equilibrium exchange rate in their model (see their eq. 15) becomes a function of the contemporaneous interest rates, the risk premium and the flow of information in the FX market.

The aim of this paper is to analyze empirically the importance of these variables for the daily dynamics of the (nominal) dinar-euro exchange rate. Unlike the previous studies and in line with the growing literature on nonlinearities in conditional means of the asset returns (Sarno and Taylor, 2003) we allow for possible nonlinear influences from the determinants to the exchange rates. Heterogeneity of agents or beliefs in the FX market, the presence of (asymmetric) transaction costs, institutional rigidities may all lead to such situations. In addition, we also include the central bank interventions and the changes in the foreign currency required reserves as potential determinants. The reason is twofold. First, a small FX market of a transition economy may show different characteristics than the markets of the major currencies which are assumed in the microstructure models. Low liquidity of the market implies potential importance of the central bank FX operations for the behavior of the FX agents. The non-inclusion of the central bank variables could, therefore, lead to the standard omitted variable bias in the estimates of the model implied determinants. Second, the framework also allows us to investigate the effectiveness of the daily sterilized interventions and the role of changes in the bank reserve policy at the high frequency level.

The present analysis is related to the literature on determinants of the nominal exchange rate in transition countries which is relatively scarce. Crespo-Cuaresma *et al.* (2005), Crespo-Cuaresma *et al.* (2008) found support for the monetary model of the exchange determination as a long-run phenomen in a panel of Central European countries. The short-run dynamics of the exchange rate however are still largely unexplained. Using a linear specification, Ardic and Selcuk (2006), Egert and Komarek (2006) showed that changes in country risk and central bank interventions are the main drivers of the nominal exchange rate returns in Turkey and the Czech Republic. On the other hand, Disyatat and Galati (2007), Scalia (2008) and Frömmel *et al.* (2011) find that at the intra-daily level macro (news) surprises and order flow have significant effects on the exchange rate behavior in the Czech Republic and Hungary.

The contribution of this paper is therefore twofold. First, to the best of our knowledge, this is the first empirical analysis of the hybrid macro-micro determinants of the daily movements in the dinar-euro exchange rate. Given the importance that the nominal exchange rate movements have on the real economy in an open transition country like

Serbia[5], identification of its determinants could provide useful information for both policy makers and market participants, including those in other transition countries with similar characteristics. Second, and different to other empirical studies, we do not impose any a priori assumption on the form of the relationship between the variables and use semiparametric techniques to estimate the relation of interest, highlighting also the benefits of such approach in comparison to standard linear models in the presence of different types of nonlinearities.

The rest of this paper is organized as follows: Section 2 presents econometric methodology, Section 3 describes the data and empirical results and Section 4 concludes the paper. All empirical results are presented in the Appendix.

II. Methodology

We use a partially linear additive model (PLAM) with (conditional) heteroscedasticity to model the determinants of the nominal exchange rate:

$$\Delta e_t = \alpha + D_t'\delta + \sum_{j=1}^{p} g_j\left(X_{t,j}\right) + \sigma_t\varepsilon_t,\ t = 1..n \qquad (1)$$

where: Δe_t is the percentage change in nominal exchange rate (log-return), $X_t \in R^p$ is a p-dimensional vector of independent variables which have a nonlinear effect on the nominal exchange rate and may also include the lagged values of Δe_t, $D_t \in R^d$ is a d-dimensional vector of independent variables that have linear influence on the exchange rate and random term ε_t is assumed to be *i.i.d.* $g_i(\cdot)$ are unspecified univariate functions of each variable $X_{t,j}$. Since we are primarily interested in the conditional mean movements we leave conditional variance σ_t^2 unspecified, but take into account conditional heteroscedasticity in the estimation of the model parameters.

Specification given in equation (1) encompasses standard linear model that can be obtained by assuming that functions $g_i(\cdot)$ are linear. The assumption that the true data generating process (dgp) in the conditional mean is linear is relatively strong. Recent empirical literature on exchange rate modelling (Sarno and Taylor, 2003) documents that nonlinear effects are important in explaining the behaviour of nominal and real exchange rates in both developed and developing countries. The common approach in all non-linear studies is to modify linear specification and estimate a particular non-linear model for the relationship of interest, often from the class of smooth transition models. This, however, again puts relatively strong assumption that the researcher knows the type of nonlinear underlying dgp.

Instead of imposing a particular type of non-linear relationship between the variables of interest we consider a semiparametric additive partially linear model given in (1). Specification (1) thus provides a flexible generalization of the linear model and allows

[5] See, for example, Hsing and Hsieh (2010) who include the exchange rate as one of the determinants of changes in the real output in Serbia. The importance of exchange rate as a determinant of the inflation rate through the exchange rate pass-through has received a considerable attention in the literature, for recent applications in transition countries see for example Cozmâncă and Manea (2010) and references therein.

one to investigate non-linear effects without imposing any structure on the type of nonlinearity. At the same time, the specification is also robust to the curse of dimensionality that arises in case of fully nonparametric estimation[6].

The model (1) is estimated using the recently proposed (Ma and Yang, 2011) spline backfitted kernel smoothing (SBKS) estimator. The estimator combines the benefits of the previously proposed spline and kernel estimators of the PLAM. Li (2000) showed that spline estimators of the PLAM, introduced by Hastie and Tibshirani (1990), are computationally efficient and consistent. However, their distributional properties remain unknown. Kernel estimators, on the other hand, have a well-defined limiting distribution, but require an additional step to control for the additive structure of the data generating process. A common approach is to use a two-step kernel marginal integration (Fan *et al.*, 1998, Fan and Li, 2003). Since kernel marginal integration requires estimation of a high dimensional nonparametric function $E(\Delta e_t|X_t)$ (without imposing additive structure) in the first step, this may introduce finite sample imprecision given the number of variables in the model, which may not be fully recovered by the second step estimation.

The SBKS estimator combines the benefits of the two approaches. In the first step, (undersmoothed) spline estimators $\overline{g}_j(\cdot)$ of the unknown functions and parameters {α, β} are obtained, thus avoiding the need for kernel estimation of high dimensional nonparametric function. Next, these estimators are used to construct "oracle" responses $\overline{\Delta e_{t,j}}$ (as if the influence of variables other then X_j were known). The good distributional properties of the kernel estimators are then exploited using a local linear regression estimation on pairs $\{\overline{\Delta e_{t,j}}, X_{t,j}\}$ to obtain the final estimate $\hat{g}_j(x_j)$.

In particular, the first step series estimation of the model in (1) is based on idea that each smooth function $g_j(x_j)$ can locally be well approximated (in the mean square sense) by a linear combination of the base functions $B_{j,s}$:

$$g_j(x_j) \approx \sum_{s=1}^{S_j} \phi_{j,s} B_{j,s}(x_j) \tag{2}$$

where: the base functions $B_{j,s}$ are assumed to be sufficiently smooth and satisfying the condition $B_{j,s}(x_j=0)=0$ in order for the functions $g_j(x_j)$ to be identified. We employ spline approximation, where $B_{j,s}(\cdot)$ are linear B-spline basis (see de Boor, 2001) and S_j denotes the number of knots. The estimates $\{\overline{\alpha}, \overline{\delta}, \overline{\phi}_{j,s}, j = 1..p;\ s = 1..S_j\}$ are obtained by minimizing the least squares criterion:

[6] The curse of dimensionality arises if the conditional mean is specified as $\Delta e_t = \alpha + D_t\delta + G(X_t)$ + + $\sigma_t\varepsilon_t$, where function $G(\cdot)$ is *p*-dimensional. Since fully non-parametric estimation of function $G(\cdot)$ is performed over the R^p space, the rate of convergence of the estimator thus depends on the dimension *p* and is much slower than $n^{1/2}$ for moderate levels of *p*, leading to potential inaccuracy of the small sample estimates and limits to the number of variables to include, see more in Fan and Yao (2003).

$$\sum_{t=1}^{n}\left(\Delta e_t - \alpha - D_t'\delta - \sum_{s=1}^{S_j}\phi_{j,s}B_{j,s}\left(X_{j,t}\right)\right)^2 \quad (3)$$

The pilot (first-step) estimators of parameters {α,β} are the least squares estimates $\{\bar{\alpha},\bar{\delta}\}$.

Pilot estimators $\bar{g}_j\left(x_j\right)$ are obtained after additional recentering as: $\bar{g}_i\left(X_{t,i}\right)=\sum_{i=1}^{S_i}\bar{\phi}_{i,s}B_{i,s}\left(X_{i,t}\right)-n^{-1}\sum_{t=1}^{n}\sum_{i=1}^{S_i}\bar{\phi}_{i,s}B_{i,s}\left(X_{i,t}\right)$.

The oracle (pseudo) responses are constructed as:

$$\overline{\Delta e_{t,j}} = \Delta e_t - \bar{\alpha} - D_t'\bar{\delta} - \sum_{i=1,i\neq j}^{p}\bar{g}_i\left(X_{t,i}\right)$$

Final estimates $\hat{g}_j(x_j)$ are obtained using a kernel regression estimator on pairs {$\overline{\Delta e_{t,j}}$, $X_{t,j}$ }. It is well known that the standard kernel regression (Nadaraya-Watson) method suffers from the poor boundary behavior and larger asymptotic bias in comparison to local linear smoothers (Fan and Gijbels, 1996). Given the importance of the large movements in explanatory variables in the second part of the sample, which are by construction located close to the boundary of the support, we use the local linear estimator to obtain $\hat{g}_j(x_j)$.

$$\hat{g}_j\left(x_j\right)=e\begin{pmatrix} S_0\left(x_j\right) & S_1\left(x_j\right) \\ S_1\left(x_j\right) & S_2\left(x_j\right)\end{pmatrix}^{-1}\begin{pmatrix} Z_0\left(x_j\right) \\ Z_1\left(x_j\right)\end{pmatrix}=S\left(x_j\right)^{-1}Z\left(x_j\right). \quad (4)$$

Here, e is a selection vector e = [0 1]. For the index k=0,1,2:

$$S_k(x_j)=n^{-1}\sum_{t=1}^{n}(X_{t,j}-x_j)^k K_b(X_{t,j}-x_j)$$

$$Z_k(x_j)=n^{-1}\sum_{t=1}^{n}(X_{t,j}-x_j)^k K_b(X_{t,j}-x_j)\overline{\Delta e_{t,j}}$$

and $K_b\left(v\right)=b^{-1}K\left(\frac{v}{b}\right)$ is kernel function with bandwidth b.

Using Theorems 1 and 2 in Ma and Yang (2011), the confidence intervals (sets) for the estimated functions (parameters) can be obtained. The constructed confidence intervals are then employed for testing linearity of each explanatory variable. Under the null hypothesis of linearity, the fitted linear function is covered by the semiparametric confidence interval. Any deviation of the linear fit outside the confidence interval thus provides evidence against the linearity of the effect of a particular variable. Although the additive partially linear model is more flexible than the (parametric) linear model it is still possible that the model is misspecified. To guard against this possibility, we test the adequacy of the additive model, which is equivalent to testing the null hypothesis:

$$H_o \ : \ E\left(\Delta e_t \mid X_t, D_t\right) = \alpha + D_t^{'}\delta + \sum_{j=1}^{p} g_j\left(X_{t,j}\right) \ a.s \tag{5}$$

for some $\delta \in R^d$ and some smooth class of functions $g_j()$. The alternative hypothesis is negation of the null. To test the null hypothesis we employ the Cramer-von Mises (CM) type of statistics proposed by Li *et al*. (2003) and consider the following test statistics[7]:

$$CM = \int_{R^p} \left| n^{1/2} \tau\left(\xi\right) \right|^2 d\chi\left(\xi\right) \tag{6}$$

where: $\tau\left(\xi\right) = n^{-1}\sum_{t=1}^{n} \hat{\varepsilon}_t W\left(X_t, \xi\right)$, $W\left(\cdot\right)$ is a pre-specified function, $\hat{\varepsilon}_t$ are the residuals from the estimation of model (1) and $d\chi\left(\xi\right)$ is a probability measure on R^p. Since the limiting distribution of the test statistics is unknown and conditional heteroscedasticity is present in the data, we employ the fixed regressor wild bootstrap (Chen and Fan, 1999) to obtain the *p*-values of the test statistics.

III. Empirical Results

III.1 Data

Daily data from 1/9/2006 to 4/6/2010 is obtained from the National Bank of Serbia (NBS) database[8]. Figure 1 depicts the evolution of the dinar-euro exchange rate over the analyzed period. Looking at the plot, two periods are easily identified. The period before September 2008 is characterized by moderate volatility and slow appreciation of dinar vis-a-vis euro, which reaches its maximum level at 75.754 on 07/08/2008. The reverse trend is observed following the debut of the world-wide financial crisis, where after initial depreciation of 22% in three months from 6/10/2008 to 9/1/2009 and temporary stabilization, dinar is slowly, but continuously depreciating throughout the period.

We consider the following set of variables as the model implied determinants of the nominal exchange rate: the volume of the interbank currency trades (excluding NBS intervention), total household savings in foreign currency, net banks' purchases of foreign currency from the foreign exchange offices (FEO) and households, the interest rate differential and the risk premium.

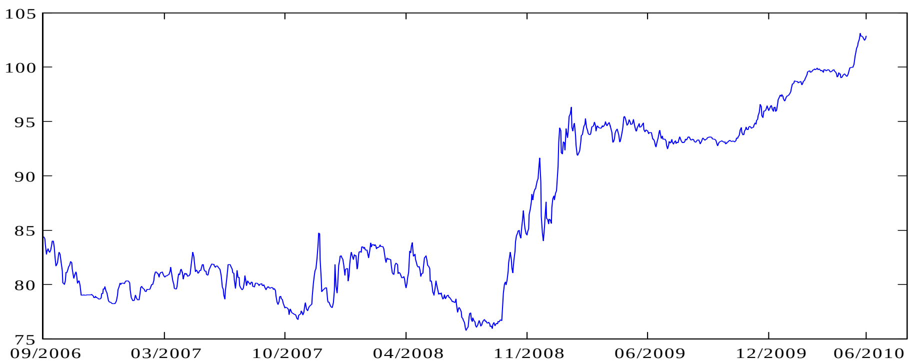
---

[7] Li *et al*. (2003) assume that the data is i.i.d. The proof of the limiting distribution with the dependent data can be established using central limit theorem for β-mixing Hilbert-valued variables, similar to Chen and Fan (1999).

[8] September 2006 marks the beginning of the free float regime of the dinar-euro exchange rate. Before that and since the beginning of transition in October 2000, the exchange rate had fixed parity before January 2003 and from January 2003 to September 2006 the exchange rate was defined through crawling peg regime.

Figure 1

The Dinar-Euro Exchange Rate



There are several theoretical explanations for the direct impact of the volume of interbank currency trades on exchange rates. The first is the mixture of distribution hypothesis (Clark, 1973), which is based on the assumption that asset prices and volumes are jointly driven by an unobserved stochastic process. If more information arrives to the market in a given time interval, the prices would respond more strongly. That implies the existence of a contemporaneous relationship between the exchange rate returns and trading volumes. The second theory is the sequential information arrival model (Copeland, 1976), where new information becomes available to one investor at a time. Due to sequential information flow, current and lagged values of trading volume can convey useful information about future exchange rates. Both arguments are related to the concept of order flow and the information processing in the foreign exchange market as discussed in Lyons (1995, 2001), Evans and Lyons (2002, 2008) and Evans (2010). In particular, they find that a significant part of surprises about fundamentals is transmitted to exchange rates via order flow and that this channel is more important in explaining short-run movements in exchange rates than direct modelling of the news. Since order flows data is unavailable for the period of study, using the volume of the interbank currency trades can be viewed as a proxy for information processing in the dinar-euro market[9]. Given the characteristics of the Serbian economy, we use two additional variables in relation to information processing and daily pressures on the FX market. Due to the high level of euroization of the economy, a significant part of household savings is euro-denominated and, hence, may have short-run effects on the foreign exchange market in the presence of low liquidity. McKinnon (1982) showed that higher degree of dolarization may lead to more instability in the nominal exchange rate and stronger depreciation expectations. This in turn may impact depreciation of the actual exchange rate, depending on the expectation formation mechansim and the level of liquidity in the market (see for

[9] Note that order flow data typically covers only a limited segment of the FX markets (i.e., transactions of one or few FX dealers), so that it may not be entirely representative of the market-wide flow of information.

example, Akcay *et al*., 1997, in case of Turkey). The net banks' purchases of foreign currency from the FEOs and households should capture the additional daily pressures on the currency from the non-bank savings and grey economy.

Given the low level of development of the bond market in Serbia, alternative measures of interest rate differential are required. We use overnight interest rate spread calculated as the difference between Beonia (Serbian equivalent of Eonia) and Eonia as a proxy for the interest rate differential. We have also experimented with the spread between 2-week dinar repo rate and the respective Euribor rate, as well as with the spread between the reference rates, but the variables are not found to be statistically significant. Since credit default swap (CDS) spreads for Serbia are not available for the entire sample period we use Emerging Market Bond Index (EMBI) and change in the index as a proxy for changes in perceived country risk. Figures 2-4 present the evolution of the selected variables over time.

Figure 2

Volume of Interbank Trades (EUR million); Household Savings (EUR billion)

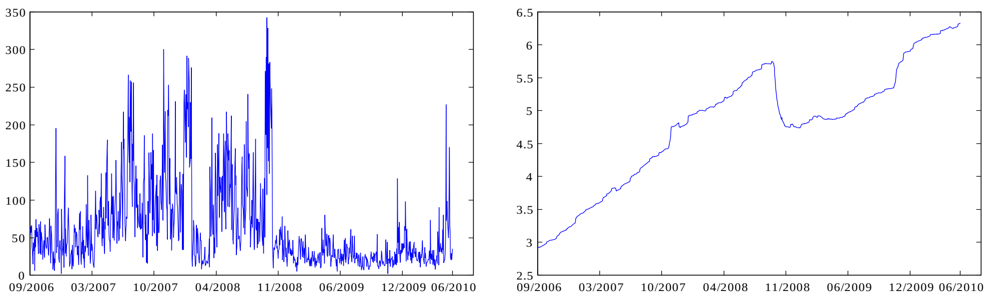


Figure 3

Net Purchases from FEO and Household (EUR million); EMBI Index

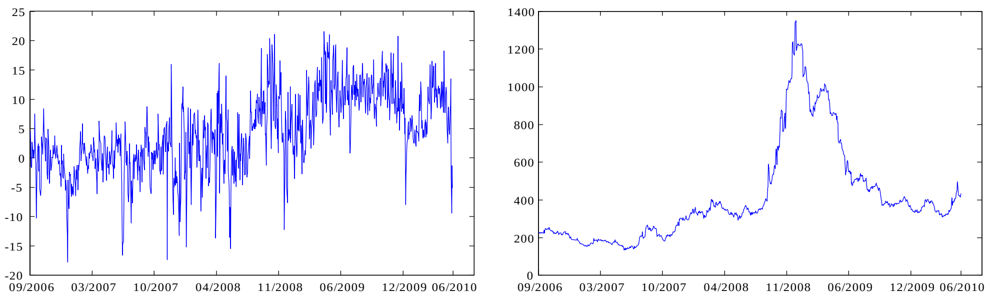
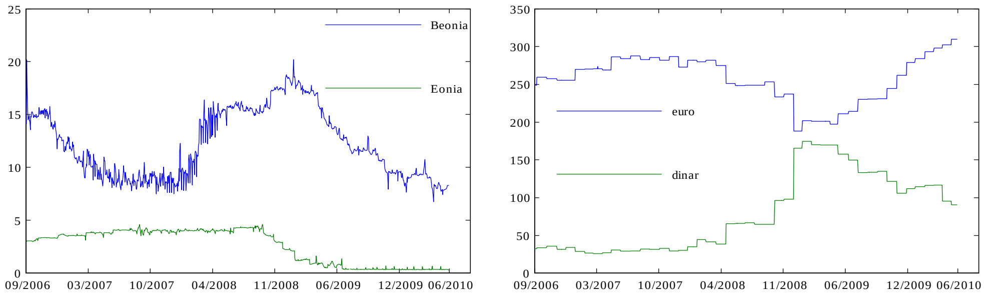


Figure 4

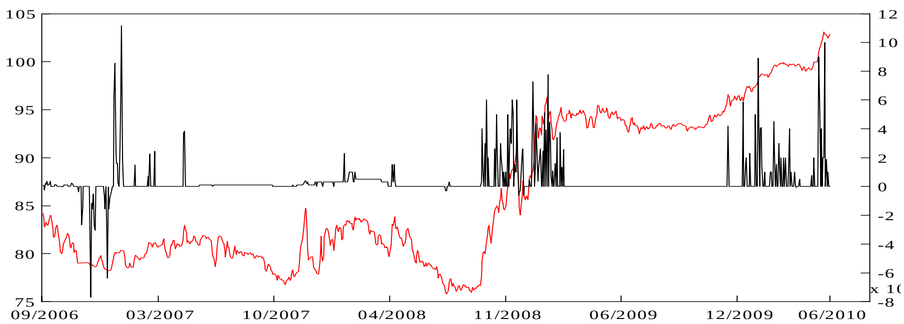
Beonia and Eonia Index; Banks' Dinar and Euro Required Reserves (RSD billions)



The second set of variables that we consider are the instruments used by the NBS: volume of daily interventions in the foreign exchange market and changes in banks' euro-denominated required reserves[10]. A sterilized central bank intervention can influence the daily exchange rate movements through a variety of channels (see Sarno and Taylor (2003), Chapter 7). In this paper, we are interested in the aggregate effect that interventions have on the exchange rates. In the sample, NBS intervened on 357 days in total (327 days were net purchases of dinar and 30 days were net sales) with the average amount of 11.35 (14.73, respectively) million EUR. Figure 5 shows the interventions and the corresponding exchange rates on the day following the intervention in line with the fact that the official exchange rate e_t on day t is defined as the average rate from transactions on the day t-1. Figure 5 shows that most of the net sales of dinar occurred in the pre-crisis period, while the post crisis period is characterized by a larger number of net purchase interventions.

Figure 5

The RSD/EUR Exchange Rate and Intervention (10 million EUR)



[10] Since the movements in banks' dinar denominated reserves follow closely the movements in euro denominated reserves with an opposite sign we do not include both variables to avoid potential multicolinearity.

III.2 Formulation of the Model

Given a potential structural break in the series at the beginning of the recent crisis that would invalidate the assumption of strict stationarity, we split the sample and estimate the model separately over the two periods. The first period is from 1/9/2006 to 12/9/2008 and the second from 15/9/2008 to 4/6/2010. The break point corresponds to the collapse of Lehman Brothers. We start by testing for stationarity of variables of interest. As expected, unit root tests[11] imply that nominal exchange rates, EMBI index, overnight interest rate spread, and household savings are first difference stationary, while other variables are found to be weakly stationary. We start with the following model:

$$\Delta e_t = \alpha + \sum_{i=1}^{p_1} g_{1,i}\left(\Delta e_{t-i}\right) + \sum_{i=1}^{p_2} g_{2,i}\left(\Delta i_{t-i}\right) + \sum_{i=1}^{p_3} g_{3,i}\left(vol_{t-i}\right) + \sum_{i=1}^{p_4} g_{4,i}\left(INT_{t-i}\right) + \sum_{i=1}^{p_5} g_{5,i}\left(\Delta EMBI_{t-i}\right)$$
$$+\sum_{i=1}^{p_6} g_{6,i}\left(\Delta S_{t-i}\right) + \sum_{i=1}^{p_7} g_{7,i}\left(RR_{t-i}\right) + g_8\left(NP_{t-1}\right) + g_9\left(Temp_{t-1}\right) + \sum_{i=1}^{4} \delta_i D_{t,i} + \sigma_t \varepsilon_t$$

where: Δi_{t-1} is the change in overnight interest rate spread, vol_{t-1} is the volume of interbank trades, INT_{t-1} is the NBS intervention, $\Delta EMBI_{t-1}$ is the log-difference in perceived risk, ΔS_{t-1} is the log-change in foreign savings, NP_{t-1} is net bank purchases of foreign currency, RR_{t-1} is the required euro reserves and D_t is the day of the week dummy. We also include variable $TEMP_{t-1}$, which is the average temperature during the day in Belgrade collected from the Republic Hydrometeorological Service of Serbia in order to control for possible seasonal effects in the exchange rate. Note that given the method in which the officially reported nominal exchange rate is determined, the first lag of explanatory variables has a contemporaneous effect on the exchange rate.

The presence of contemporaneous relationships, however, introduces a potential endogeneity bias in some of the variables, as the amount of intervention at time *t-1* may depend on the evolution of the exchange rate over the same period, whose average trading value is reported as the official rate for time *t*. Likewise, the volume of trades at time *t-1* may be influenced by the movements in the exchange rate over the same period. The behaviour of other explanatory variables is less likely to be influenced by the current movements in the exchange rate. In order to control for endogeneity of intervention, we follow the instrumental variable two stage approach (Humpage, 1999, Galati *et al*., 2005, Fatum and Pedersen, 2009) and estimate a central bank reaction function in order to capture the expected component of the intervention variable and use predicted value of intervention from this estimation in place of the original intervention values. The truncated characteristic of the intervention variable as the dependent variable introduces additional problem when estimating the parameters of the reaction function, leading to potential sample selection bias in estimation. We follow Humpage (1999) and estimate the parameters through the two step procedure. In the first step, the probability of intervention is specified as a function of the deviation of today's exchange rate from the trend and the exchange rate volatility using the probit model:

[11] The results are availble on request.

$$P\left(C_t = 1 | e_t - \breve{e}_t, \sigma_t\right) = \Phi\left(\gamma_1 + \gamma_2\left(e_t - \breve{e}_t\right) + \gamma_3 \sigma_t\right) \tag{7}$$

where: C_t is the zero-one indicator variable for the decision to intervene, $\breve{e}_t$ is the trend variable computed as a 10-day moving average of the exchange rate and volatility is approximated using the rolling 10-day standard deviation of the exchange rate. We have also experimented with using 20-day trend and volatility estimates, but the obtained results are qualitatively similar. The variables determining the decision to intervene are those commonly found in empirical studies of the central bank's reaction function and are in line with an intention of the NBS to intervene in order to prevent high daily oscilations in dinar-euro rate[12]. In the second step, a simple OLS regression is performed:

$$INT_t = \beta_1 + \sum_{j=1}^{p} \beta_{2,j} INT_{t-j} + \sum_{j=0}^{p-1} \beta_{3,j} \Delta e_{t-j} + \beta_4 M_t \tag{8}$$

where: M_t is the Mills ratio from the probit estimation in order to control for the sample selection bias. The equation (8) models the amount of intervention as a function of the past interventions and the previous changes in exchange rate. The fitted values from the equation (8) are then used in place of the observed interventions. Similarly, we control for the endogeneity of the volume series using a two step IV procedure where the lagged volume and the exchange rate changes are used as instruments for the observed volume. Note that since we use a linear specification to control for the endogeneity the first step estimation error is of order $n^{-1/2}$ and, therefore, following Li and Wooldridge (2002), it can be neglected in the second step semiparametric estimation. Table 1 presents the results from two-step estimation of the NBS reaction function using heteroscedasticity robust standard errors. Both variables in probit equation are found to be statistically significant. The volume of intervention, in turn, depends on the past intervention values (the so-called intervention clustering phenomenon) and on the past changes in exchange rate. The R^2 from the OLS regression in both samples is relatively high (for time series estimation) and significantly higher than the values reported in Humpage (1999) and Galati *et al*. (2005). As a result, we can be relatively confident that the weak instrument problem is not present.

Table 1

Estimates of the NBS Reaction Function

Variable	Subsample 1	Subsample 2
Probit equation		
γ_1	-0.318***	-1.422***
e_t-$\breve{e}_t$	11.781 ***	21.634 ***
δ_t	51.184 ***	81.021 ***
Intervention equation		
β_1	0.138	1.804***
INT_{t-1}	0.525***	0.062

[12]Another reason to pursue intervention may be to increase liquidity in the foreign exchange market with a small depth. However, without utilizing high frequency data with the exact timing of the intervention it is not possible to capture the importance of this channel. The values of the previous day volumes are not found to be statistically significant in the probit equation.

Variable	Subsample 1	Subsample 2
INT_{t-2}	-0.121	0.098*
INT_{t-4}	-0.029	0.137**
INT_{t-5}	0.085*	0.012
Δe_{t-1}	13.749***	72.005***
Δe_{t-2}	6.545	-28.818**
Δe_{t-4}	5.602*	9.819
M_t	-0.035	-0.945***
R^2	0.324	0.328

The specification (1) potentially includes a large number of variables as all lags of the variables are treated as separate variables in semiparametric estimation. In order to obtain a parsimonious representation of the model, we employ Huang and Yang (2004) *BIC* criterion to select variables for semiparametric estimation. We follow the (adjusted) three step procedure from Jansen *et al*. (2008), where we assume that all continuous variables from specification (1) are present in the semiparametric model for Δe_t:

Step (i): start with one predictor variable and determine the lag order for that variable. Specifically, choose p_{11} to minimize *BIC* for $1\leq p_{11}\leq P$, where *P* is the pre-specified maximum lag length. Next, choose p_{11} and p_{12} to minimize *BIC* for $1\leq p_{11}, p_{12} \leq P$ (here p_{11} may or may not equal the value obtained in the previous search, depending on the dimensionality of the problem). Conduct a sequence of such searches until the addition of one additional lag no longer improves the model fit.

Step (ii): Given the lag order structure for the first variable, determine the lag structure for the second predictor variable using the same procedure as in step (i). Given the lag structures for the first two variables, specify the lag order for the third variable. Finally, proceed with inclusion of other (non-lagged) variables.

Step (iii): Repeat steps (i)-(ii) for different orderings of the predictor variables.

III.3 Results

We start from the specification in (5) and use *BIC* to select the significant variables where we set the maximum lag length $P=5$. We perform the selection procedure separately over the two subsamples. The number of interior knots in spline estimation is fixed to five. The bandwidth parameter in local linear estimation is set as $b_j=c_j std(X_j)n^{-1/5}$ where $std(X_j)$ is the sample standard deviation of the variable X_j and constant c_j is selected via generalised cross-validation with 50 grid points. We used standard quartic kernel in estimation. Since the asymptotic variance of $\hat{g}_j(x_j)$ depends on the unknown quantities which need to be separately (nonparametrically) estimated, the confidence intervals are obtained through boostrap. We use fixed regressor wild boostrap with 1000 bootstrap repetitions in order to control for conditional heteroscedasticity in the data (Yang, 2008). The confidence intervals are obtained as the appropriate percentiles of the boostrap distribution at each evaluation point x_j.

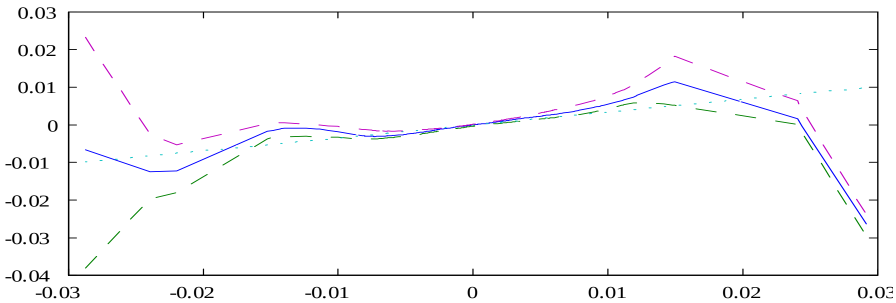
The results from estimation together with the 5% confidence bands are presented in Figures 6-7 and Table 2. On each plot, the values of the independent variable are on the *x*-axis and the corresponding value of the effect on exchange rate returns is given on *y*-axis. Table 2 presents estimates of the parameters from the linear part. We only present the results for the variables selected by *BIC*.

In the first subsample, characterized by moderate volatility and small medium run appreciation, we find evidence of significant nonlinearity in the autoregressive part of the model. In addition, we find that changes in savings in foreign currency (which almost tripled over the period) and banks' net purchases of foreign currency had significant effect on the exchange rate. The other variables are not found to improve the model fit via the *BIC* criterion (the final value of *BIC* is -10.72). The finding is related to the stability of the exchange rate over the first subsample and characteristics of the Serbian economy at an early transition stage. In particular, the significance of the lagged exchange rate returns implies a certain degree of inefficiency of the foreign exchange market (see, e.g., Gradojevic *et al*., 2010), using a different statistical approach). The shape of the estimated coefficient function implies a degree of mean-reverting behaviour of the exchange rate where smaller positive changes in the one period lagged exchange rate (depreciation) are associated with the further depreciation of the exchange rate, but the large past depreciations have appreciation effect.

Figure 6

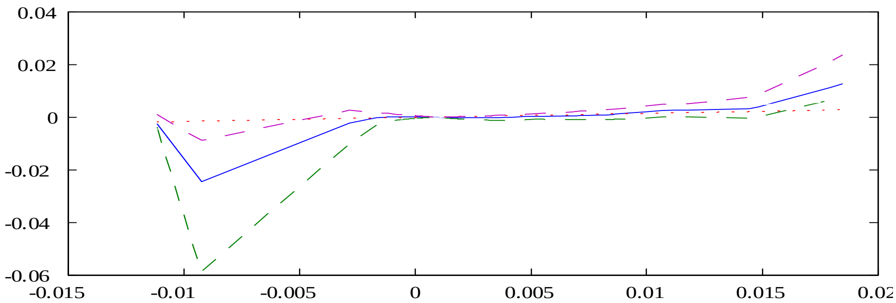
Plots of the SBKS Estimator (Solid Lines), Bootstrap Confidence Intervals (Dashed Lines), Linear Regression Estimator (Dotted Lines):

Figure 6.1. One Period Lagged Change in Exchange Rate



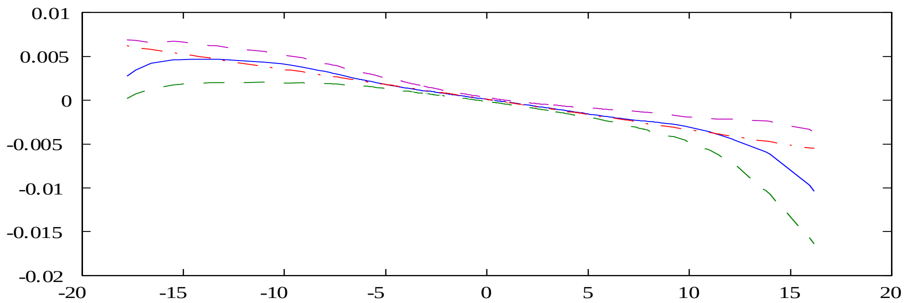
:

Figure 6.2. Savings in Foreign Currency



The influence of changes in foreign currency-denominated savings and net bank purchases likely stems from the high level of euroization of the economy and large amount of foreign currency in non-bank channels and grey economy. Increase in foreign currency savings results in increased demand for foreign currency leading to the depreciation pressures in the presence of low market liquidity. Conversely, negative changes in foreign currency savings lead to appreciation pressures, although the trend is reversed for large negative changes, which may signal a loss of confidence in the banking system and less demand for home currency. Analogously, changes in bank's net purchases signal the importance of the unofficial channels in the economy and its effects on the foreign exchange demand. As Figure 6.3 shows, the null that the net bank purchases have a linear effect is not rejected and the final specification incorporates this variable in the linear part of the model together with day of the week effects, while semiparametric estimates of the nonlinear part are those presented in Figures 6.1-6.2. The presence of the semi-parametric component does not allow computation of R^2 as the standard measure of the fit and to gauge the relative success of the model we compute the correlation between the fitted values and observed values of the exchange rate returns.

Figure 6.3. Net Foreign Currency Purchases by Banks



The correlation between the fitted and observed values when the net bank purchases enter the model linearly is 0.669, implying a relatively good fit of the model. We then test whether additive partially linear model adequately captures nonlinearities in the data by computing the Li *et al*. (2003) test. We choose $W(X_t, \xi) = \exp(iX_t'\xi)$ and $d\chi(\xi)$ to be standard normal *p*-variate vector, which yields a simple closed form expression for the underlying integral (Escanciano, 2007). The statistics has 0.738 as value and running the 1000 bootstrap replications yields 1.412 critical value and 0.72 corresponding *p*-value. Therefore, we fail to reject the additive partially linear model for the first subsample.

Table 2

Estimates of the Linear Part

Variable	Subsample 1	Subsample 2
A	-0.0013**	-0.0261**
D_1	0.0018**	0.0007
D_2	0.0020**	0.0004
D_3	0.0014 **	0.0001
D_4	0.0010**	-0.0005
NP_{t-1}	-0.0004**	-0.0002**
$EMBI_{t-1}$	-	0.0179**

*Notes: *,**,*** imply significance at the 10%, 5% and 1% level.*

The set of influential variables is larger in the second subsample. Results are reported in Figure 7, where we find that in addition to autoregression effects, country risk, banks' net purchases, volume of interbank trades, interest rate differential and NBS intervention have effect on the dinar-euro rate. Conversely, the changes in foreign currency savings and the required reserve are not found to improve the fit (the final value of *BIC* is -10.63). Also, we find no support for the seasonal effects using temperature as a proxy (the length of the subsamples may be too small to capture the seasonal effects). The effect of banks' net purchases is presented in Figure 7.1 and is of smaller magnitude relative to the first subsample, although the null of linearity is again not rejected. Figure 7.2 plots the estimated coefficient function with respect to changes in the country risk. We can see a small degree of nonlinearity in response of the exchange rate to changes in the EMBI index.

Figure 7

Plots of the SBKS Estimator (Solid Lines), Bootstrap Confidence Intervals (Dashed Lines), Linear Regression Estimator (Dotted Lines)

Figure 7.1. Net Foreign Currency Purchases by Banks

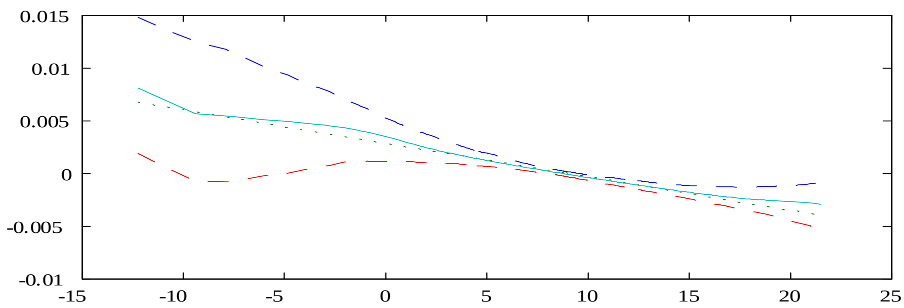
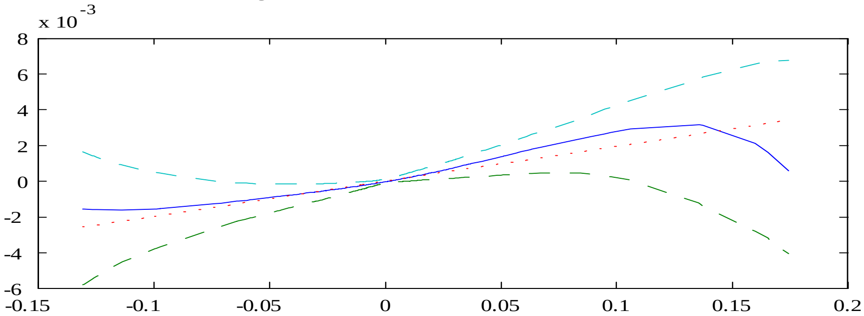


Figure 7.2. The EMBI Index



The positively slopped linear fit cannot be rejected at the 5% significance level, implying that larger changes in the EMBI index have proportionally larger effect towards depreciation. Given the evidence of linearity in the first two variables the model is re-estimated with inclusion of these variables in the linear part of the model and the results are reported in Table 2. We do not find statistically significant day of the week effects in the second subsample. As expected, the estimated parameters for country risk and net banks' purchases are significant at the 5% level (boostrapped confidence interval).

Estimates of the nonlinear part are given in Figures 7.3-7.6. Results in Figure 7.3 imply that the information from the contemporaneous interbank trade volumes have effect on the exchange rate movements. Smaller trade volumes have effect towards appreciation, while larger volumes lead to proportionally larger dinar depreciation. Note that foreign exchange market in Serbia is mostly demand driven (supply of foreign currency is relatively stable). Thus, smaller demand for euro results in smaller trade volumes and leads to appreciation of dinar while the opposite holds in case of large demand for euros. Figure 7.4 plots the estimated autoregression coefficient function. As in the first subsample, it implies the presence of inefficiencies in the foreign exchange market, while the magnitude of the estimated coefficients is smaller relative to the first subsample signalling the importance of other factors in the second period. Figure 7.5 shows that the NBS interventions were effective over this period. The effect is nonlinear and depends on the size of the intervention, where larger sales of euros have stronger appreciation effect on dinar, which is in line with a signalling effect that large sales have over the most recent period. The impact of interventions on the exchange rate movements comes with a two day lag, while the inclusion of the contemporaneous value of intervention does not improve the fit of the model. This is in line with the evidence on (lagged) effectiveness of interventions in other transition countries (Egert and Komarek, 2006, Disyatat and Galati, 2007). Finally, in Figure 7.6 we plot the effect of changes in the overnight interest rate spread. The effect is positive and larger for negative changes in the spread. Negative changes in overnight spread lead to the standard carry-trade type effect on the exchange rate. Depreciation effects from increases in the spread over the period can be associated with the increase in the liquidity risk premium and consequently smaller capital inflows.

Figure 7.3. Volume in the Foreign Exchange Market

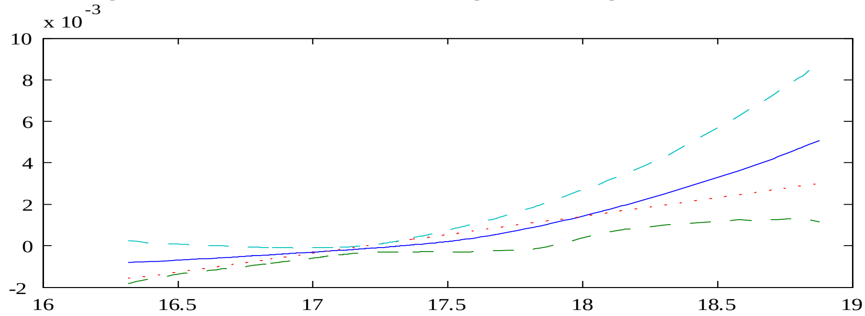
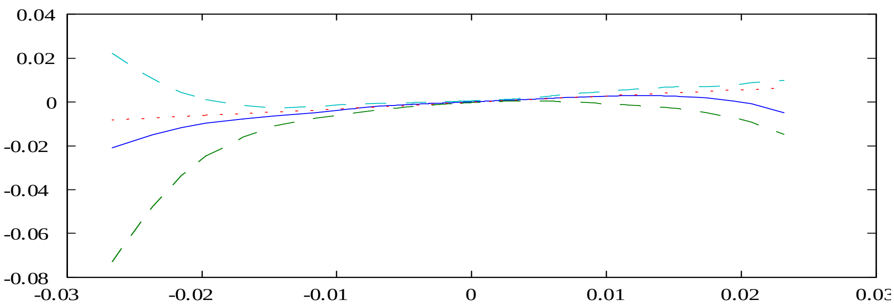


Figure 7.4. One Period Lagged Change in Exchange Rate



To assess the adequacy of the model in the second subsample we again perform Li, *et al*. (2003) test using 1000 bootstrap replications and obtain 0.61 *p*-value. The correlation between the fitted and observed values is 0.586.

Figure 7.5. Two Periods Lagged Intervention

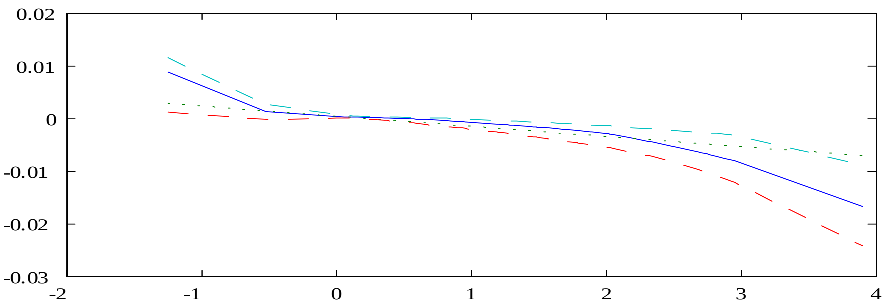
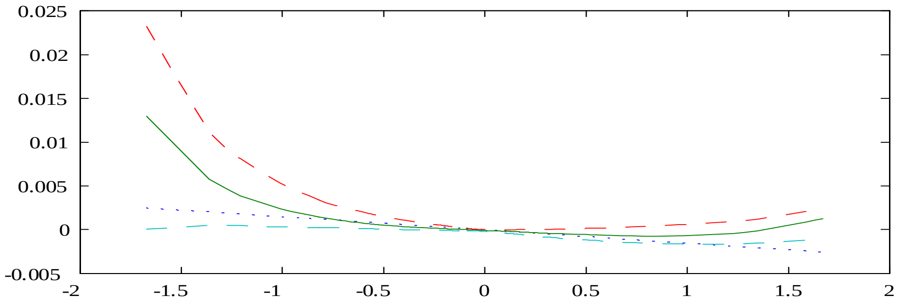


Figure 7.6. Overnight Interest Rate Spread



IV. Conclusions and Future Research

In this paper, we have studied drivers of daily dynamics of the nominal Serbian dinar-euro exchange rate from September 2006 to June 2010 using linear and nonlinear statistical models. We identified several factors influencing the daily exchange rate changes. In the period before the financial crisis, in addition to information in past returns, changes in household savings and banks' net purchases of foreign currency have statistically significant explanatory power, where the influence of the former two variables is highly nonlinear. These points to the low efficiency of the Serbian FX market even in the presence of heterogeneous agents. Moreover, the results suggest the lack of information processing in the FX market (at least through the trade volume) and rejection of the hybrid models of the exchange rate determination at daily level over the period of relative stability (both of the economy and the FX market). From September 2008 onwards other factors gain importance. In particular, changes in country's risk, volume of interbank trades and the interest rate spread are associated with depreciation of dinar, while the importance of the factors from the previous period diminishes. The evidence is supportive for the hybrid models suggesting that in times of higher uncertainty the dinar-euro exchange rate reacts stronger and in a non-linear manner to changes in observed macro variables and new information in the FX market. As expected, the model also captures negative country premium effects on the exchange rate. In addition, the results imply different degree of response of the exchange rate to the NBS measures. We do not find any evidence that changes in the required reserves have effect on the FX movements suggesting the absence of the exchange rate channel of monetary transmission for this monetary policy instrument, at least at the daily level. Conversely, the NBS interventions are found to be effective with a time delay over the crises period only. This suggests some role for the active exchange rate management as on days following the sales of euros against dinars, market participants tended to put more weight on a stronger dinar. Moreover, the size of the intervention plays a role as larger interventions have progressively stronger effect on the exchange rate movements.

There is a lot more work to be done in the present framework. First, due do data limitation, we have not included any macro (news) surprises in the model. As discussed in the main text, to the extent the news are captured in the daily volume series (Evans, 2010) this should not affect our results, but this needs to be empirically validated. Second, we have only included a proxy for Serbia's country risk. Exchange rates of some of the neighbouring countries with free float have experienced a similar behavior as the dinar. For example, the Romanian leu depreciated from 3.673 lei per euro on 12/09/2008 to 4.225 on 04/06/2010, with a similar time pattern. The Hungarian forint also depreciated in the same period with a rapid 31% drop between September 2008 and March 2009. This implies that broader set of regional risks might have influence on the exchange rate; however, we abstract from the inclusion of EMBI indices for other countries given its high correlation with EMBI index for Serbia (correlations between EMBI index for Serbia and those for Bulgaria, Ukraine and Turkey is above 0.9 in both subsamples). Further research is required to capture additional measures of the regional risk. Third, we used a simple linear approach to control for potential endogeneity of intervention and volume variable. A semi-parametric approach to control for endogeneity is an extension that can be of interest beyond the present paper.

References

Akçay, O.C. Alper, C.E. and Karasulu, M., 1997. Currency Substitution and Exchange Rate Instability: The Turkish case. *European Economic Review,* 41, pp.827-835.

Ardic, O. and Selcuk, F., 2006. The Dynamics of a Newly Floating Exchange Rate: the Turkish Case. *Applied Economics*, 38, pp.931-941.

Chen, X. and Fan, Y., 1999. Consistent Hypothesis Testing in Semiparametric and Nonparametric Models for Econometric Time Series. *Journal of Econometrics,* 91, pp.373-401.

Cheung, Y. Chinn, M. and Garcia-Pasqual, A., 2005. Empirical Exchange Rate Models of the Nineties: Are any Fit to Survive. *Journal of International Money and Finance,* 24, pp.1150-1175.

Clark, P.K., 1973. A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices. *Econometrica,* 41*, pp.*135--55.

Copeland, T. 1976. A Model of Asset Trading under the Assumption of Sequential Information Arrival. *Journal of Finance,* 45*,* pp.379-395.

Cozmâncă, B. and Manea, F., 2010. Exchange Rate Pass-Through into Romanian Price Indices. A VAR Approach. *Romanian Journal of Economic Forecasting,* 13(3), pp.26-52.

Crespo-Cuaresma, J. Fidrmuc, J. and MacDonald, R., 2005. The Monetary Approach to Exchange Rates in the CEECs. *Economics of Transitition,* 13, pp.395-416.

Crespo-Cuaresma, J. Fidrmuc, J. and Silgoner, M., 2008. Fundamentals, the Exchange Rate and Prospects for the Current and Future EU Enlargements: evidence from Bulgaria, Croatia, Romania and Turkey. *Empirica,* 35, pp.195-211.

de Boor, C., 2001. *A Practical Guide to Splines*. Springer Verlag.

Disyatat, P. and Galati, G., 2007. The Effectiveness of Foreign Exchange Intervention in Emerging Market Countries; Evidence from the Czech Koruna. *Journal of International Money and Finance,* 26, pp.383-402.

Égert, B. and Komárek, L., 2006. Foreign Exchange Interventions and Interest Rate Policy in the Czech Republic: Hand in Glove? *Economic Systems,* 30, pp.121-140.

Escanciano, J.C., 2007. Model Checks Using Residual Marked Empirical Processes. *Statistica Sinica,* 17*,* pp.115-138.

Evans, M.D., 2010. Order Flows and The Exchange Rate Disconnect Puzzle. *Journal of International Economics,* 80. *pp.*58-71.

Evans, M.D. and Lyons, R.K., 2002. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy, 110*. pp.170-180.

Evans, M.D. and Lyons, R.K., 2008. How Is Macro News Transmitted to Exchange Rates?. *Journal of Financial Economics,* 88, pp.26-50.

Fan, J. and Gijbels, I., 1996. *Local Polynomial Modelling and its Applications*. Chapman and Hall, London.

Fan, J. and Yao, Q., 2003. *Nonlinear Time Series: Nonparametric and Parametric Methods.* Springer Series in Statistics.

Fan, J. Härdle, W. and Mammen, E., 1998. Direct Estimation of Low Dimensional Components in Additive Models. *Annals of Statistics,* 26*,* pp.943-971.

Fan, Y. and Li, Q. 2003. A Kernel-based Method for Estimating Additive Partially Linear Models. *Statistica Sinica,* 13*,* pp.739--762.

Fatum, R. and Pedersen, J., 2009. Real-Time Effects of Central Bank Interventions in the Euro Market. *Journal of International Economics,* 78, *pp.*11-20.

Frömmel, M. Kiss, M.K. and Pintér, K., 2011. Macroeconomic Announcements, Communication and Order Flow on the Hungarian Foreign Exchange Market. *International Journal of Finance and Economics,* 16, pp.172-188.

Galati, G. Melick, W. and Micu, M., 2005. Foreign Exchange Market Intervention and Expectations: The Yen/Dollar Exchange Rate. *Journal of International Money and Finance,* 24, *pp.*982-1011.

Gradojević, N. Djaković, V. and Andjelić, G., 2010. Random Walk Theory and Exchange Rate Dynamics in Transition Economies. *Paneconomicus,* 57, pp.303-320.

Hastie, T.J. and Tibshirani, R.J., 1990. *Generalized Additive Models.* Chapman & Hall, London.

Hsing, Y. and Hsieh, W.J., 2010. Responses of Real Output in Serbia to the Financial and Global Economic Conditions. *Romanian Journal of Economic Forecasting,* 13(3), *pp.*107-114.

Huang, J. and Yang, L., 2004. Identification of Nonlinear Additive Autoregressive Models. *Journal of the Royal Statistical Society Series B,* 66, pp.463-477.

Humpage, O.W., 1999. U.S. Intervention: Assessing the Probability of Success. *Journal of Money, Credit and Banking,* 31*,* pp.731-47.

Jansen, D.W. Li, Q. Wang, Z. and Yang, J., 2008. Fiscal Policy and Asset Markets: A Semiparametric Analysis. *Journal of Econometrics,* 147*,* pp.141-150.

Li, Q., 2000. Efficient Estimation of Additive Partially Linear models. *International Economic Review,* 41, pp.1073-1092.

Li, Q. and Wooldridge, J., 2002. Semiparametric Estimation of Partially Linear Models for Dependent Data with Generated Regressors. *Econometric Theory,* 18*,* pp.625-645.

Li, Q. Hsiao, C. and Zinn, J., 2003. Consistent Speciation Tests for Semiparametric/Nonparametric Models Based on Series Estimation Methods. *Journal of Econometrics,* 112*,* pp.295-325.

Lyons, R.K., 1995. Tests of Microstructural Hypotheses in the Foreign Exchange Market. *Journal of Financial Economics,* 39, pp.321-351.

Lyons, R.K., 2001. *The Microstructure Approach to Exchange Rates.* MIT Press.

Ma, S. and Yang, L., 2011. Spline-backfitted Kernel Smoothing of Partially Linear Additive Model. *Journal of Statistical Planning and Inference,* 141, pp.204-219.

McKinnon, R.I., 1982. Currency Substitution and Instability in the World Dollar Standard. *American Economic Review,* 72, pp.320-333.

Sarno, L. and Taylor, M.P., 2003. *Exchange Rate Economics.* Cambridge University Press.

Scalia, A., 2008. Is foreign exchange intervention effective? Some microanalytical evidence from the Czech Republic. *Journal of International Money and Finance,* 27, pp.529–546.

Yang, L., 2008. Confidence Band for Additive Regression Model. *Journal of Data Science,* 6*,* pp.207-217.