DEPARTMENT OF ECONOMICS

EUI Working Papers

ECO 2011/21
DEPARTMENT OF ECONOMICS

EXCHANGE RATES AND FUNDAMENTALS: CO-MOVEMENT, LONG-RUN RELATIONSHIPS AND SHORT-RUN DYNAMICS

Stelios Bekiros

EUROPEAN UNIVERSITY INSTITUTE, FLORENCE
DEPARTMENT OF ECONOMICS

Exchange Rates and Fundamentals: Co-Movement, Long-Run Relationships and Short-Run Dynamics

STELIOS BEKIROS

EUI Working Paper **ECO** 2011/21

ISSN 1725-6704

Printed in Italy
European University Institute
Badia Fiesolana
I – 50014 San Domenico di Fiesole (FI)
Italy
www.eui.eu
cadmus.eui.eu

EXCHANGE RATES AND FUNDAMENTALS: CO-MOVEMENT, LONG-RUN RELATIONSHIPS AND SHORT-RUN DYNAMICS

Stelios Bekiros *

European University Institute, Department of Economics,
Via della Piazzuola 43, I-50133 Florence, Italy

ABSTRACT

The present study builds upon the seminal work of Engel and West [2005, Journal of Political Economy 113, 485-517] and in particular on the relationship between exchange rates and fundamentals. The paper discusses the well-known puzzle that fundamental variables such as money supplies, interest rates, outputs etc. provide help in predicting changes in floating exchange rates. It also tests the theoretical result of Engel and West (2005) that in a rational expectations present-value model, the asset price manifests near–random walk behaviour if the fundamentals are I(1) and the factor for discounting future fundamentals is near one. The study explores the direction and nature of causal interdependencies and cross-correlations among the most widely traded currencies in the world, their country-specific fundamentals and their US-differentials. A new VAR/VECM-GARCH multivariate filtering approach is implemented, whilst linear and nonlinear non-causality is tested on the time series. In addition to pairwise causality testing, several different groupings of variables are explored. The methodology is extensively tested and validated on simulated and empirical data. The implication is that although exchange rates and fundamentals appear to be linked in a way that is broadly consistent with asset-pricing models, there is no indication of a prevailing causal behaviour from fundamentals to exchange rates or vice-versa. When nonlinear effects are accounted for, the evidence implies that the pattern of leads and lags changes over time. These results may influence the greater predictability of currency markets. Overall, fundamentals may be important determinants of FX rates, however there may be some other unobservable variables driving the currency rates that current asset-pricing models have not yet captured.

Keywords: simulation-based inference; causality; random walk; filtering; nonlinearity; asset-pricing

JEL classification: F31; F37; C52; C53

---

* I am grateful to Massimiliano Marcellino for helpful comments and discussions. This research is supported by the Marie Curie Intra European Fellowship (FP7-PEOPLE-2009-IEF, N° 251877) under the 7th European Community Framework Programme. The usual disclaimers apply.
Tel.: +39 055 4685916; *Fax*: +39 055 4685 902; *E-mail address*: stelios.bekiros@eui.eu

1. INTRODUCTION

In their seminal work Engel and West (2005) deal with the long-standing puzzle in international economics, i.e., the difficulty of linking floating exchange rates to macroeconomic fundamentals. It might well be that the exchange rate is determined by such fundamental variables, but in many occasions FX rates are in fact well approximated as random walks. Meese and Rogoff (1983a, 1983b) first established the result that fundamental variables do not help predict future changes in exchange rates. They evaluated the out-of-sample behaviour of several models of exchange rates, using data from the 1970s. They found that forecast accuracy generally increased when the assumption of unchanged exchange rate was employed, compared to the predictions from the exchange rate models. While a large number of studies have subsequently claimed to find success for various versions of fundamentals-based models, sometimes at longer horizons and over different time periods, the success of these models has not proved to be robust. Cheung *et al.* (2002) show that no particular model/specification is very successful and conclude that it may be that one model will do well for one exchange rate, and not for another. Engel and West (2005) show analytically that in a rational expectations present-value model, an asset price manifests near–random walk behaviour if fundamentals are $\mathrm{I}(1)$ and the factor for discounting future fundamentals is near one. They also argue that the data do exhibit a related link suggested by standard models and that the exchange rates help predict fundamentals. The implication is that exchange rates and fundamentals are linked in a way that is broadly consistent with asset-pricing models of the exchange rate.

The present study builds upon the seminal work of Engel and West (2005), and in particular on the relationship between exchange rates and fundamentals. In this paper a new line of attack is taken on the question of linear and nonlinear causality and co-movement between FX rates and fundamentals. The conventional class of asset-pricing models of Engel and West (2005) is utilized, in which the exchange rate is the expected present discounted value of a linear combination of observable fundamentals and unobservable shocks. Linear driving processes are posited for fundamentals and shocks. In their work Engel and West (2005) present a theorem concerning the behaviour of an asset price determined in a present-value model. They show that in the class of present-value models, asset prices will follow a process arbitrarily close to a random walk if at least one forcing variable has a unit autoregressive root and the discount factor is near unity. So, in the limit, as the discount factor approaches unity, the change of the asset price in time *t* will be uncorrelated with information known at time *t-1*. Hence, as the discount factor approaches unity the model puts relatively more weight on fundamentals far into the future in order to estimate the asset price. Transitory shocks in the fundamentals become less important than the permanent components. As the discount factor approaches one, the variance of the change of the discounted sum of the random walk component approaches infinity, whereas the variance of the change of the stationary component approaches a constant. Whether a discount factor of 0.9 or 0.99 is required to deliver a process statistically indistinguishable from a random walk depends on the sample size used to test for random walk behaviour and the entire set of model parameters. Engel and West (2005) present some correlations calculated analytically in a simple stylized model. This study begins by presenting correlations estimated from simulations based on the simple stylized model of Engel and West (2005). A simple univariate process for fundamentals is assumed, with parameters chosen to reflect data from recent floating periods and discount factors from 0.5 to 0.95, the latter of which suffice to yield near-zero correlations between the period *t* and *t-1*. An attempt is made to verify the theoretical conclusion of Engel and West (2005) that large discount factors account for random walk behaviour in exchange rates.

Moreover, the important question of model validation arises from the FX rate unpredictability implied by the random walk behaviour of the present-value models. Surely much of the short-term fluctuation in FX rates is driven by changes in expectations about the future. Assuming that the models are good approximations and that expectations reflect information about future fundamentals, the exchange rate changes will be useful in forecasting these fundamentals. In other words, exchange rates Granger-cause the fundamentals. Engel and West (2005) find a unidirectional Granger causality from exchange rates to fundamentals and a far weaker causality from fundamentals to exchange rates. Overall, the statistical significance of the predictability is not uniform and suggests a link between exchange rates and fundamentals that perhaps is modest in comparison with the links among other economic variables. In this study the validity of Engel and West (2005) results is investigated as well as implications are discussed of a possible unidirectional causality running from exchange rate to fundamentals and vice-versa, or of a dynamic bi-directional causality. The plausibility of their conclusions is explored also in terms of cointegration detection and application of nonlinear forecasting models (Taylor *et al.*, 2001; Kilian and Taylor 2003). Evidence is provided in the literature of forecasting changes in exchange rates at longer horizons using nonlinear methods. MacDonald and Taylor (1994), Chinn and Meese (1995) and Mark (1995) have all reported success in forecasting FX rates at longer horizons imposing long-run restrictions from monetary models. Groen (2000) and Mark and Sul (2001) find greater success using panel methods. Kilian and Taylor (2003) suggest that models which incorporate nonlinear mean reversion can improve the forecasting accuracy of fundamentals models, though it proved difficult to detect the improvement in out-of-sample forecasting exercises. Thus, it seems natural to pursue the question of whether exchange rates can forecast fundamentals. This paper investigates the validity of the results in Engel and West (2005) also in the direction of possible forecasting applications.

In regard to causality detection, the Granger test (Granger, 1969) is used as a benchmark in the literature. Basically, it assumes a parametric linear, time series model for the conditional mean. However, this test is sensitive only to causality in the conditional mean while covariables may influence the conditional distribution of the time series in nonlinear ways. Baek and Brock (1992) noted that parametric linear Granger causality tests have low power against certain nonlinear alternatives. In view of this, nonparametric techniques have been applied with success because they place direct emphasis on prediction without imposing a linear functional form. The test by Hiemstra and Jones (1994) which is a modified version of the Baek and Brock (1992) test is regarded as a test for a nonlinear dynamic causal relationship. This test is employed in the present project in order to detect the direction and nature of causalities between exchange rates and fundamentals.

The research methodology in this paper incorporates theoretical implications, extensive simulations and empirical applications. Based on the simple stylized model of Engel and West (2005) and via Monte Carlo simulations, the correlation structure between fundamentals and exchange rates for various discount factors is revealed. First, an attempt is made to confirm the theoretical conclusion of Engel and West (2005) that large discount factors lead to random walk behaviour in exchange rates. Then, the direction and nature of causalities (linear or nonlinear) among the different exchange rates is investigated using levels, returns and a second-moments measure (conditional volatility), both on the simulation-driven and empirical time series. The empirical study examines the most liquid and widely traded currencies in the world (also known as "FX majors") as well as the outdated German mark. Many country-specific fundamental drivers are explored including money, consumer price index, interest rate, industrial production etc., as well as their differentials with the US.

The rest of the paper is organized as follows. Section 2 briefly reviews the linear Granger causality framework and provides a description of the nonparametric test for nonlinear causality. Section 3 presents a new multivariate VAR/VECM-GARCH filtering approach for causality detection. In section 4, extensive Monte Carlo simulations are presented based on the stylized model of Engel and West (2005). Section 5 describes the data and section 6 presents the empirical results. Finally, section 7 summarizes and concludes.

2. CAUSALITY TESTING

In this study linear and nonlinear causality detection is performed via the Granger test and the modified Baek-Brock (1992) test, respectively. The conventional approach of causality testing is based on the Granger test (Granger, 1969), which assumes a parametric, linear model for the conditional mean. This specification is simple and appealing as the test is reduced to determining whether the lags of one examined variable enter into the equation of the other, albeit it requires the linearity assumption. In this setup, vector autoregressive residuals are sensitive only to causality in the conditional mean while co-variables may affect the conditional distribution in nonlinear patterns. Baek and Brock (1992) noted that the parametric linear Granger causality test has low power against certain nonlinear alternatives or higher moments. As a result, nonparametric causality tests have been proposed in the literature directly emphasizing on prediction without imposing a linear functional form. Hiemstra and Jones (1994) proposed a modified Baek-Brock test. It is a causality-in-probability test for nonlinear dynamic relationship which is applied to the residuals of vector autoregressions and it is based on the conditional correlation integrals of lead–lag vectors of the variables. This test relaxes Baek and Brock's assumption of *i.i.d* time series and instead allows each series to display weak (or short-term) temporal dependence. It can detect the nonlinear causal relationship between variables by testing whether past values influence present and future values. In what follows, the two causality tests are formally described.

2.1 Granger causality test

The linear Granger causality test (Granger, 1969) is based on a reduced-form vector autoregression (VAR) model. If $\mathbf{y}_t = \left[y_{1t},\ldots,y_{\ell t}\right]$ is the vector of endogenous variables and ℓ the number of lags, the VAR(ℓ) model is given by

$$\mathbf{y}_t = \sum_{s=1}^{\ell} \Phi_s \mathbf{y}_{t-s} + \varepsilon_t \qquad (1)$$

where Φ_s is the $\ell \times \ell$ parameter matrix and ε_t the residual vector, for which $E(\varepsilon_t) = \mathbf{0}$ and $E(\varepsilon_t \varepsilon_s^{'}) = \begin{cases} \varepsilon_\varepsilon & t = s \\ \mathbf{0} & t \neq s \end{cases}$. In case of the stationary time series $\{x_t\},\{y_t\}$ the bivariate VAR is

$$\begin{aligned} x_t &= \Phi(\ell)x_t + \mathrm{X}(\ell)y_t + \varepsilon_{x,t} \\ y_t &= \Psi(\ell)x_t + \Omega(\ell)y_t + \varepsilon_{y,t} \end{aligned} \qquad t = 1,2,\ldots,N \qquad (2)$$

where $\Phi(\ell), \mathrm{X}(\ell), \Psi(\ell)$ and $\Omega(\ell)$ are lag polynomials with roots outside the unit circle and the error terms are *i.i.d.* processes with zero mean and constant variance. The test whether y strictly Granger causes x is simply a test of the joint restriction that all coefficients of the lag polynomial $\mathrm{X}(\ell)$ are zero, whilst a test of whether x strictly Granger causes y is a test regarding $\Psi(\ell)$. In the unidirectional case the null hypothesis of no Granger causality is rejected if the exclusion restriction is rejected, whereas if both $\mathrm{X}(\ell)$ and $\Psi(\ell)$ joint tests for significance are different from zero the series are bi-causally related. However, in order to explore possible effects of cointegration a vector autoregression model in error correction form (Vector Error Correction Model-VECM) is estimated using the methodology developed by Engle and Granger (1987) and expanded by Johansen (1988) and Johansen and Juselius (1990). The bivariate VECM model has the following form

$$\begin{aligned} \Delta x_t &= -p_1\left(\begin{bmatrix}1 & -\lambda\end{bmatrix}\cdot\begin{bmatrix}y_{t-1} & x_{t-1}\end{bmatrix}^T\right) + \Phi(\ell)\Delta x_t + \mathrm{X}(\ell)\Delta y_t + \varepsilon_{\Delta x,t} \\ \Delta y_t &= -p_2\left(\begin{bmatrix}1 & -\lambda\end{bmatrix}\cdot\begin{bmatrix}y_{t-1} & x_{t-1}\end{bmatrix}^T\right) + \Psi(\ell)\Delta x_t + \Omega(\ell)\Delta y_t + \varepsilon_{\Delta y,t} \end{aligned} \qquad t = 1,2,\ldots,N \qquad (3)$$

where $\begin{bmatrix}1 & -\lambda\end{bmatrix}$ the cointegration row-vector and λ the cointegration coefficient. Thus, in case of cointegrated time series $\{x_t\}$ and $\{y_t\}$ linear Granger causality should be investigated on $\mathrm{X}(\ell)$ and $\Psi(\ell)$ via the VECM specification.

2.2 Nonparametric nonlinear causality test

Let Θ_{t-1} denote an information set and $F\left(x_t \middle| \Theta_{t-1}\right)$ the conditional probability distribution of x_t given the information set Θ_{t-1}, which consists of an L_x-length lagged vector of x_t, $\mathbf{x}_{t-L_x}^{L_x} \equiv \left(x_{t-L_x}, x_{t-L_x+1}, \ldots, x_{t-1}\right)$ and an L_y-length lagged vector of y_t, $\mathbf{y}_{t-L_y}^{L_y} \equiv \left(y_{t-L_y}, y_{t-L_y+1}, \ldots, y_{t-1}\right)$. Hiemstra and Jones (1994) tested the following null hypothesis for a given pair of lags L_x and L_y

$$H_0 : F\left(x_t \middle| \Theta_{t-1}\right) = F\left(x_t \middle| \Theta_{t-1} - \mathbf{y}_{t-L_y}^{L_y}\right) \qquad (4)$$

Denoting the m-length lead vector of $\mathbf{x}_t^m \equiv \left(x_t, x_{t+1}, \ldots, x_{t+m-1}\right)$, for $t \in \mathbf{Z}$, the claim made by Hiemstra and Jones (1994) is that the null hypothesis given in Eq. (4) implies for all $\varepsilon > 0$

$$\begin{aligned} P\left(\left\|\mathbf{x}_t^m - \mathbf{x}_s^m\right\| < \varepsilon \,\middle|\, \left\|\mathbf{x}_{t-L_x}^{l_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{l_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ = P\left(\left\|\mathbf{x}_t^m - \mathbf{x}_s^m\right\| < \varepsilon \,\middle|\, \left\|\mathbf{x}_{t-L_x}^{l_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon\right) \end{aligned} \qquad (5)$$

For the time series of realizations $\{x_t\}$ and $\{y_t\}$, $t = 1, \ldots, T$, the nonparametric test consists of choosing a value for ε typically in $[0.5,\ 1.5]$ after unit variance normalization, and testing Eq. (5) by expressing the conditional probabilities in terms of the corresponding ratios of joint probabilities

$$\begin{aligned} C_1\left(m + L_x, L_y, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{m+L_x} - \mathbf{x}_{s-L_x}^{m+L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{L_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ C_2\left(L_x, L_y, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{L_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon, \left\|\mathbf{y}_{t-L_y}^{L_y} - \mathbf{y}_{s-L_y}^{L_y}\right\| < \varepsilon\right) \\ C_3\left(m + L_x, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{m+L_x} - \mathbf{x}_{s-L_x}^{m+L_x}\right\| < \varepsilon\right) \\ C_4\left(L_x, \varepsilon\right) &\equiv P\left(\left\|\mathbf{x}_{t-L_x}^{L_x} - \mathbf{x}_{s-L_x}^{L_x}\right\| < \varepsilon\right) \end{aligned} \qquad (6)$$

Thus, Eq. (5) can be formulated as

$$\frac{C_1\left(m+L_x,L_y,\varepsilon\right)}{C_2\left(L_x,L_y,\varepsilon\right)}=\frac{C_3\left(m+L_x,\varepsilon\right)}{C_4\left(L_x,\varepsilon\right)} \qquad (7)$$

Using correlation-integral estimators and under the assumptions that $\{x_t\}$ and $\{y_t\}$ are strictly stationary, weakly dependent and satisfy the mixing conditions of Denker and Keller (1983), Hiemstra and Jones (1994) showed that

$$\sqrt{n}\left(\frac{C_1\left(m+L_x,L_y,\varepsilon,n\right)}{C_2\left(L_x,L_y,\varepsilon,n\right)}-\frac{C_3\left(m+L_x,\varepsilon,n\right)}{C_4\left(L_x,\varepsilon,n\right)}\right)\sim N\left(0,\sigma^2\left(m,L_x,L_y,\varepsilon\right)\right) \qquad (8)$$

with $\sigma^2\left(m,L_x,L_y,\varepsilon\right)$ as given in an appendix. One-sided critical values are used based on this asymptotic result, rejecting when the observed value of the test statistic in Eq. (8) is too large.

3. VAR/VECM-GARCH FILTERING

This study presents a multi-step methodology for examining dynamic relationships between exchange rates and fundamentals as well as among exchange rates. Initially, the nonlinear and linear dynamic linkages are explored through the application of the nonparametric nonlinear test, and the Granger causality test after controlling for cointegration. Then, after filtering the series using the properly specified VAR or VECM model, the residuals are examined by the modified Baek-Brock test. In addition to applying the usual bivariate VAR or VECM model to each pair of time series, residuals of a full-variate model are also considered to account for the possible effects of the other variables. In this way any remaining causality is strictly nonlinear in nature, as the VAR or VECM model has already purged the residuals of linear dependence. Finally, in the last step, the null hypothesis of nonlinear non-causality is investigated after controlling for conditional heteroskedasticity in the data using a multivariate GARCH-BEKK model again both in a bivariate and in a full model representation. Thus, the short-run movements are accounted for and the volatility persistence mechanism is captured.

The use of the nonlinear test on filtered data with a multivariate GARCH model enables to determine whether the utilized model is sufficient to describe the relationship among the series. Consequently, the statistical evidence of nonlinear Granger causality would be strongly reduced when the appropriate multivariate GARCH model is fitted to the raw or linearly filtered data. However, failure to accept the no-causality hypothesis may also constitute evidence that the selected multivariate GARCH model is mispecified[1]. In general, many GARCH models can be used for second-moment filtering. The present study employs the GARCH-BEKK model. Considering $\{y_t\}$ to be a vector stochastic return process of dimension $\mathrm{N}\times 1$ and ω a finite vector of parameters, let $y_t = \mu_t(\omega) + \varepsilon_t$ where $\mu_t(\theta)$ is the conditional mean vector and $\varepsilon_t = H_t^{1/2}(\omega) z_t$ where $H_t^{1/2}(\omega)$ is a $N\times N$ positive definite matrix. The random vector z_t has $E(z_t)=0$ and $Var(z_t)=I_N$ as the first two moments where I_N is the identity matrix. Hence, H_t is the conditional variance matrix of y_t. It is difficult to guarantee the positivity of H_t in the VEC-GARCH representation of Bollerslev *et al*. (1988) without imposing strong restrictions on the parameters. Engle and Kroner (1995) proposed a new parametrization of H_t that imposes its positivity, namely the Baba-Engle-Kraft-Kroner (BEKK) model. The full *BEKK(1, 1, K)* model is defined as:

$$H_t = A^{*\prime} A^* + \sum_{k=1}^{K} B_k^{*\prime} \varepsilon_{t-1} \varepsilon_{t-1}' B_k^* + \sum_{k=1}^{K} C_k^{*\prime} H_{t-1} C_k^* \qquad (9)$$

where A^*, B_k^* and C_k^* are $N\times N$ matrices but A^* is upper triangular. The summation limit K determines the generality of the process and the sufficient conditions to identify BEKK models are that $B_{k,11}^*, C_{k,11}^*$ and the diagonal elements of A^* are restricted to be positive. To reduce the number of parameters in the BEKK(1,1,1) model and consequently to reduce the generality, a diagonal BEKK model can be imposed, i.e. B_k^* and C_k^* in (8) are diagonal matrices. The maximum likelihood method is used to estimate the BEKK model.

4. MONTE CARLO SIMULATIONS

Let s_t be the asset price expressed as a discounted sum of current and expected future fundamentals. The examined asset-pricing model is of the form

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t\left(a_1' x_{t+j}\right) + b\sum_{j=0}^{\infty} b^j E_t\left(a_2' x_{t+j}\right), \quad 0 < b < 1 \qquad (10)$$

[1] This line of analysis is similar to the use of the univariate BDS test on raw data and on GARCH models (Brock *et al*., 1996; Brooks, 1996; Hsieh, 1989)

where $\mathbf{x}_t$ is the $n \times 1$ vector of fundamentals, b is a discount factor, and a_1 and a_2 are $n \times 1$ vectors. Campbell and Shiller (1987) and West (1988) consider this model for stock prices where s_t is the level of the stock price, x_t the dividend (a scalar), $a_1 = 0$ and $a_2 = 1$. The log-linearized model of Campbell and Shiller (1988) also has this form, where s_t is the log of the stock price, x_t is the log of the dividend and $a_1 = 1$, $a_2 = 0$. In this study s_t is the log of the exchange rate and $\mathbf{x}_t$ contains such variables as interest rates and logs of prices, money supplies etc. Assume that at least one element of the vector $\mathbf{x}_t$ is an $\mathrm{I}(1)$ process, with the Wold innovation being a $n \times 1$ vector ε_t. Engel and West (2005) require that either (1) $a_1' x_t \sim \mathrm{I}(1)$ and $a_2 = 0$ or (2) $a_2' x_t \sim \mathrm{I}(1)$, with the order of integration of $a_1' x_t$ essentially unrestricted ($\mathrm{I}(0), \mathrm{I}(1)$, or identically zero). In either case, for b near one, Δs_t is well approximated by a linear combination of the elements of the unpredictable innovation ε_t. Moreover, as suggested by Engel and West (2005) there is continuity in the autocorrelations in the sense that for b near one the autocorrelations of Δs_t will be near zero if the condition that certain variables are $\mathrm{I}(1)$, is replaced with the condition that those variables are $\mathrm{I}(0)$ but with an autoregressive root very near one.

In this study the correlation structure of exchange rates and fundamentals is estimated from simulations based on the simple stylized model of Engel and West (2005). A simple univariate process for fundamentals is assumed, with parameters chosen to reflect data from recent floating periods and discount factors from 0.5 to 0.95, the latter of which suffice to yield near-zero correlations between the periods *t-1* and *t*. Overall, an attempt is made to simulatively verify the theoretical conclusion of Engel and West (2005) that large discount factors account for random walk behaviour in exchange rates. The results of simulations are depicted in Tables 1-3. The model used is a simplified version of Eq. (10), i.e., $s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t x_{t+j}$ or $s_t = b\sum_{j=0}^{\infty} b^j E_t x_{t+j}$. The fundamentals variable x_t follows an AR(2) process with autoregressive roots φ_1 and φ. When $\varphi_1 = 1.0$, $\Delta x_t \sim$ AR(1) with parameter φ and in the limit, as $b \to 1$, each of the correlations approaches zero. The setup of the simulations is the following: x_t=1500 observations are simulated with j=5000 forward steps to the future. Thus, in total a path of 6500 observations is produced. Next, the first burn-out 500 points are discarded. The final examined processes for x_t (fundamental), s_t (FX series) and z_t (another FX series) include 1000 observations. Then correlations are computed, the paths are replicated 2000 times and the mean, median and mode of the correlations are produced. Columns 4-9 present correlations of Δs_t with time *t-1* information when x_t follows a scalar univariate AR(2). Either $a_1 = 0$ and $a_2 = 1$ or $a_1 = 1$ and $a_2 = 0$ can be assumed. These two possibilities can be considered interchangeably as for given $b < 1$, the autocorrelations of Δs_t are not affected by whether or not a factor of $1 - b$ multiplies the present value of fundamentals. Rows 1–9 in Tables 1-3 assume that $x_t \sim \mathrm{I}(1)$, specifically $\Delta x_t \sim$ AR(1) with parameter φ. For $b = 0.5$ the autocorrelations in columns 4–6 and the cross correlations in columns 7–9 are significant, whereas for $b = 0.9$, they are dramatically smaller. Finally, from rows 10–13 it can be inferred that if the unit root in x_t is replaced by an autoregressive root of 0.9 or higher, the autocorrelations and cross-correlations of Δs_t are not much changed. Overall, Tables 1-3 provide very similar results to the ones produced analytically by Engel and West (2005).

Next, results from an extensive cross-correlation and causality exercise are presented with the use of stepwise multivariate filtering, on the simulated series that correspond to rows 1-3 and 7-9 of Tables 1-3 (i.e., with $b = 0.5$ and $b = 0.95$). The causality analysis is conducted at the *5%* and *1%* significance level and it involves the utilization of three paradigms, namely between the simulated currency and fundamentals series, between two different currency series as well as two different FX series with the same fundamentals driver. The case of cointegration is also investigated via the Johansen trace statistic in order to use the right specification for the Granger causality testing, i.e., VAR or VECM. Also, the second-moment filtering is conducted via a GARCH-BEKK model. The results are presented in Tables 4-6. The mode, mean and median of the correlations are presented. In all cases the GARCH filtering on the VAR/VECM residuals purges all linkages between the examined series. The numbers presented for causality results are the percentages of the Granger-caused series detected. It appears that cointegration results vary among the investigated paradigms. The case of two different FX series presents the lowest percentages, whereas the Granger-causality investigation reveals a unidirectional causality link from fundamentals to FX series. This corroborates with the theoretical and empirical result of Engel and West (2005). In the other two cases the causality results are qualitatively similar for both directions, while the percentage detected is higher in case of the two different FX series with the same fundamentals driver. These results on the simulated series will be juxtaposed with the empirical results in section 6.

Finally, a forecasting exercise is conducted with various asset-pricing autoregressive models using the data generating processes produced by the simulations (Table 7). The three-step filtering methodology for examining dynamic relationships is implemented in each step of the causality estimation via a rolling window for the out-of-sample forecasting exercise. Specifically, four AR(1) specifications are used with the lagged variable being the FX series ($s_t = \beta s_{t-1} + \varepsilon_t$), the fundamentals series ($s_t = \gamma x_{t-1} + \varepsilon_t$) and the FX series with the same and different fundamental driver ($s_t = \zeta z_{t-1} + \varepsilon_t$ and $s_t = \delta z_{t-1} + \varepsilon_t$). In addition, two AR(1) specifications employing both a lagged fundamental and an FX series with the same and different fundamental driver ($s_t = \gamma_1 x_{t-1} + \gamma_2 z_{t-1} + \varepsilon_t$ and $s_t = \beta_1 x_{t-1} + \beta_2 z_{t-1} + \varepsilon_t$) are used. The out-of-sample measure is the RMSE and in particular the RMSE ratios are reported against the first AR(1) specification which is used as a benchmark. The simulated series again correspond to rows 1-3 and 7-9 of Tables 1-3, that is with $b = 0.5$ and $b = 0.95$. Also, the mode, mean and median is reported. The best out-of-sample performance is indicated for the AR(1) specification employing a lagged fundamental and an FX series with the same fundamental driver. The worst was observed for the AR(1) specification with the lagged variable being the fundamental series, while the other models yield similar results with their predictability being close to the one of the benchmark.

5. DATA

The data comprises monthly foreign exchange rates denoted relative to United States dollar (USD), namely Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. These are the most liquid and widely traded currency pairs in the world and make up about 90% of total Forex trading worldwide. The data covers the Great Moderation period, the dot-com bubble, and the period just before the outbreak of the 2007-2010 financial crisis, which was triggered by a liquidity shortfall in the US banking system. The country-specific fundamentals are the seasonally adjusted money supply m, the industrial production y (used as a proxy for the real, seasonally adjusted gross domestic product), the consumer price index (CPI) p, the three-month rate i, while the $m-y$ (=Money-IP) variable is also considered. Datastream is the source of the data. All data but interest rates is converted by taking logs and multiplying by 100. The Chow-Lin method (1971) was used to interpolate the AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate the JPY^{i}. Additionally, an asterisk used as superscript denotes the corresponding measure of fundamentals in the United States relative to the country-specific, i.e., the symbol *(*)* denotes the non-US value in the differentials. The differentials are $\left(m-m^{*}\right)$, $\left(p-p^{*}\right)$, $\left(i-i^{*}\right)$, $\left(y-y^{*}\right)$, $\left[m-y-\left(m^{*}-y^{*}\right)\right]$.

Correlations and causalities are investigated on the Δ *(differentials)*. Overall, the examined period is in levels 4/1986–7/2008, while for the Euro it spans 1/1999–7/2008.

6. EMPIRICAL RESULTS

In this section, the implications of the asset-pricing models of Engel and West (2005) are empirically investigated, as well as the hypothesis that asset price might help to predict the fundamentals or vice-versa is tested. The causal relationships between the FX rates and the five measures of fundamentals are investigated. As in Engel and West (2005), many autoregressive specifications are utilized, e.g., pairwise, tri-variate, four-variate as well as the full systems of variables (5x5). Additionally, the empirical results are juxtaposed with the Monte Carlo simulations. The statistical significance is presented at the *5% (*)* and *1% (**)* levels. The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic (Johansen, 1991). In their work Engel and West (2005) concluded that it will probably not do great violence to assume lack of cointegration and so they used for all VAR models four lags[2]. Instead, in this paper

[2] They consider lack of cointegration to be evidence that unobserved variables such as real demand shocks, real money demand shocks, or possibly even interest parity deviations have a permanent component, or at least are very persistent. Yet, it may be that the data they used to measure the economic fundamentals have some errors with permanent or very persistent components. For example, it may be

cointegration tests were conducted between the exchange rate and each of the fundamentals differentials in all specifications. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors)*. For testing reasons linear Granger causality was further investigated on the VAR/VECM and GARCH residuals, but it was no longer detected. The nonlinear causality is investigated with the modified Baek-Brock test and the number of lags used are $\ell_X = \ell_Y = 1$. The second moment filtering is performed with a GARCH-BEKK (1,1) model.

The results for all examined multivariate specifications are depicted in Tables 8-21. For the pairwise investigation, the variables included in the VAR/VECM model are $\left\{\Delta s,\ \Delta\left(m-m^*\right),\ \Delta\left(p-p^*\right),\ \left(i-i^*\right),\ \Delta\left(i-i^*\right),\ \Delta\left(y-y^*\right),\ \left[\Delta\left(m-m^*\right)-\Delta\left(y-y^*\right)\right]\right\}$. In this case VAR(1,0) is identified except VAR(2,0) in GBP $^{\Delta s - \Delta\left(m-m^*\right)}$, GBP $^{\Delta s - \Delta\left(m-m^*\right)}$ and DM $^{\Delta s - \left(i-i^*\right)}$. VECM (2,1) is identified in all cointegrated pairs except AUD $^{\Delta s - \Delta\left(i-i^*\right)}$, which is VECM(1,1). Based on the results there is no consistent evidence that exchange rates predict fundamentals after examining linear and nonlinear causal interdependencies. Some bidirectional links also appear but for different fundamentals each time. Overall, the evidence is modest that there exists a prevailing direction in the examined causalities, i.e., that either exchange rates help to predict fundamentals, or the ability of fundamentals to predict exchange rates is stronger. This result is not in full accordance with Engel and West (2005) who observe a stronger unidirectional linkage in favour of exchange rate predictability. Of course there were some major economic and non-economic developments during the sample that might perturb any consistent relationships. Several of the European countries' exchange rates and monetary policies became more tightly linked in the 1990s because of the evolution of the European Monetary Union, Germany's economy was transformed dramatically in 1990 because of reunification, the dot-com bubble hit the global economies in the mid-90s, while the Asian crisis of 1997 caused a turmoil in the international FX markets. Interestingly, two consistent results emerge from the investigation, namely that (1) linear and nonlinear links differ significantly in all examined specifications and that (2) after multivariate GARCH filtering most of the nonlinear interdependencies are purged. This indicates that the nonlinear causality is largely due to simple volatility effects. Some

---

that the appropriate measure of the money supply has permanently changed because of numerous financial innovations over the sample, so that the money supply series varies from the "true" money supply by some I(1) errors.

remaining nonlinear causalities imply that FX rates may exhibit statistically significant higher-order moments or that other multivariate GARCH models could capture the transmission mechanism of the volatility shocks more efficiently.

In addition to causality testing for the bivariate VAR/VECMs, cointegration and causality tests based on other VAR/VECM specifications are performed. Several different combinations of variables are included in the VAR/VECM models. Six groupings were tested:

1. $\left\{\Delta s,\ \Delta\left(m-m^*\right),\ \Delta\left(p-p^*\right),\ \Delta\left(i-i^*\right),\ \Delta\left(y-y^*\right)\right\}$
2. $\left\{\Delta s,\ \Delta\left(p-p^*\right),\ \Delta\left(i-i^*\right),\ \Delta\left(y-y^*\right)\right\}$
3. $\left\{\Delta s,\ \Delta\left(m-m^*\right),\ \Delta\left(p-p^*\right),\ \Delta\left(y-y^*\right)\right\}$
4. $\left\{\Delta s,\ \Delta\left(p-p^*\right),\ \Delta\left(i-i^*\right),\ \Delta\left(y-y^*\right)\right\}$
5. $\left\{\Delta s,\ \Delta\left(p-p^*\right),\ \Delta\left(y-y^*\right)\right\}$ and
6. $\left\{\Delta s,\ \Delta\left(m-m^*\right),\ \Delta\left(y-y^*\right)\right\}$

For the first grouping the number of lags identified and the cointegrating vectors presented as *(lags, coint. vectors)* are {GBP(5,1), JPY(4,1), CHF(8,1), AUD(3,1), CAD(4,1), DM(2,2), EUR(1,0)}. In case of the second the number of lags and the cointegrating vectors are {GBP(1,0), JPY(1,0), CHF(5,1), AUD(1,0), CAD(1,0), DM(2,2), EUR(2,1)} while for the third they are {GBP(5,2), JPY(4,1), CHF(2,1), AUD(2,0), CAD(4,1), DM(2,1), EUR(1,0)}. For the fourth these are {GBP(1,0), JPY(1,0), CHF(1,0), AUD(1,0), CAD(1,0), DM(1,0), EUR(2,0)}, while for the last two specifications they are {GBP(2,1), JPY(1,0), CHF(1,0), AUD(1,0), CAD(1,0), DM(2,1), EUR(1,0)} and {GBP(1,0), JPY(2,1), CHF(2,1), AUD(1,0), CAD(1,0), DM(1,0), EUR(2,1)} respectively. Linear and nonlinear causality tests were conducted for the null that Δs does not Granger-cause each of the fundamentals or the fundamentals as a group, and conversely. The results are similar to those from the bivariate VAR/VECMs. There is no consistent evidence that causality runs from the fundamentals to the exchange rates. In total, the evidence is not conclusive that there exists a prevailing direction in the examined causalities. Again, linear and nonlinear links differ significantly whilst multivariate GARCH filtering purged most of the nonlinear interdependencies. The evidence is far from overwhelming, but overall there does not appear to be a link from FX rates to fundamentals going in the direction that FX rates help forecast fundamentals, as advocated by Engel and West (2005).

7. CONCLUSIONS

Engel and West (2005) argued that when standard exchange rate models are plausibly calibrated, they have the property that the FX rates should nearly follow a random walk. Evidence that the exchange rate change is not predictable is an implication of the models, albeit observing that FX rates follow random walks is not a very complete validation of the models. Another possible explanation of the random walk behaviour of exchange rates could be that they are dominated by unobservable shocks which are well approximated by random walks. The fundamentals may not be important determinants of FX rates, and instead there may be some other variable that models have not captured or that is unobserved that drives the currency rates. Campbell and Shiller (1987) observe that when a currency variable is the present value of a fundamentals variable, then either (1) FX rate Granger-causes fundamentals relative to the bivariate information set consisting of their lags or (2) FX rate is an exact distributed lag of current and past values of the fundamental variable. Nonetheless, exchange rate models must allow for unobservable fundamentals. Failure to find Granger causality from the FX rate to the observable variables no longer implies an obviously restriction that the FX rate is an exact distributed lag of observables. It is clear, that a finding of Granger causality is supportive of a view that FX rates are determined as a present value that depends in part on observable fundamentals.

The results of this paper provide some counterbalance to the suitability - especially in the short run - of rational expectations present-value models of currency rates that became predominant since Meese and Rogoff (1983a, 1983b). Extensive Monte Carlo simulations in this work provide evidence that FX rates may incorporate information about future fundamentals. It was shown that under some assumptions the inability to forecast exchange rates is a natural implication of the models, which suggests that innovations in the FX rates ought to be highly correlated with news about future fundamentals. This relationship was also reported in the study of Andersen *et al.* (2003), who found strong evidence of exchange rate reaction to news in intraday data and in a direction consistent with standard models. The analytical results of Engel and West

(2005) have been corroborated, in that if discount factors are large (and fundamentals are $I(1)$), then it may not be surprising that present-value models cannot out-perform in terms of forecastability the random walk model of exchange rates.

Yet, a conclusive support for the link between fundamentals and the exchange rate in the direction that exchange rates can help forecast the fundamentals was not found, as in Engel and West (2005). Whilst in some cases and under certain vector autoregressive modelling there was evidence of this directional predictability, a generic result cannot be drawn. It might be that exchange rates and fundamentals are linked in a way that is broadly consistent with asset pricing models of the exchange rate, but no evidence was found of a prevailing direction in the examined causalities, i.e., that either exchange rates help to predict fundamentals, or the ability of fundamentals to predict exchange rates is stronger. Specifically, the empirical findings in this study do not fully accord with the results of Engel and West (2005) on the weak causality from exchange rates to fundamentals. Indeed there are several caveats. First, while the results from simulations are consistent with the implications of the present-value models - that exchange rates should be useful in forecasting future economic variables - there might be other possible explanations for the discrepancy in the empirical findings. It may be, for example, that currencies might Granger-cause money supplies because monetary policy makers react to the exchange rate in setting the money supply. Thus, the present-value models are not the only models that imply Granger causality from exchange rates to other economic variables. In general the results from simulations provided evidence on the correlation of exchange rate changes with the change in the expected discounted fundamentals, as well as that the Granger causality results are generated by the present-value models.

Moreover, the empirical results are not uniformly strong and overall the evidence is inconclusive that there exists a prevailing direction in the examined causalities. Additionally, linear and nonlinear links differ significantly and multivariate GARCH filtering purged most of the nonlinear interdependencies. This indicates that the nonlinear causality is largely due to simple volatility effects. Some remaining nonlinear causalities imply that FX rates may exhibit statistically significant higher-order moments or other multivariate GARCH models could capture the transmission mechanism of the volatility shocks more efficiently. As opposed to Engel and

West (2005) cointegration was detected between exchange rates and fundamentals. In accordance with the exchange rate literature, there was not much evidence that the exchange rate is explained only by the "observable" fundamentals. However, observables do not obviously dominate exchange rate changes and it is perhaps unrealistic to believe that only observable fundamentals affect currency rates.

Finally, the results of this study may also help explain the near-random walk behaviour and the causality structure of other asset prices and their markets (equities, bonds etc.) Theoretically, asset prices follow random walks only under very special circumstances. An empirical investigation of the causal behaviour of a variety of asset prices could be an interesting line of future research.

REFERENCES

Andersen, T., G., Bollerslev, T., Diebold, F. and Vega, C., 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review* 93, 38–62.

Baek, E. and Brock, W., 1992. A general test for non-linear Granger causality: bivariate model. *Working paper*, Iowa State University and University of Wisconsin, Madison, WI.

Bollerslev, T., Engle, R.F. and Wooldridge, J.M., 1988. A capital asset pricing model with time varying covariances. *Journal of Political Economy* 96, 116–131.

Brock, W.A., Dechert, W.D., Scheinkman, J.A. and LeBaron, B., 1996. A test for independence based on the correlation dimension. *Econometric Reviews* 15(3), 197-235.

Brooks, C., 1996. Testing for nonlinearities in daily pound exchange rates. *Applied Financial Economics* 6, 307-317.

Campbell, J.Y. and Shiller, R.J., 1987. Cointegration and Tests of Present Value Models. *Journal of Political Economy* 95, 1062–1088.

Campbell, J.Y., and Shiller, R..J., 1988. Stock Prices, Earnings, and Expected Dividends. *Journal of Finance* 43, 661–676.

Cheung, Y.-W., Chinn, M.D. and Pascual, A.G., 2002. Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?. *Working Paper* no. 9393, NBER, Cambridge, MA.

Chinn, M.D., and Meese, R.A., 1995. Banking on Currency Forecasts: How Predictable Is Change in Money?. *Journal of International Economics* 38, 161– 178.

Chow, G. and Lin, A.L., 1971. Best linear unbiased distribution and extrapolation of economic time series by related series. *Review of Economic and Statistics* 53(4), 372-375.

Denker, M., and Keller, G., 1983. On U-statistics and von-Mises statistics for weakly dependent processes. *Zeitschrift fur Wahrscheinlichkeitstheorie und Verwandte Gebiete* 64, 505-522.

Engel, C., and West, K.D., 2005. Exchange Rates and Fundamentals. *Journal of Political Economy* 113, 485-517.

Engle, R.F. and Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation, and testing. *Econometrica* 55(2), 251–276.

Engle, R.F. and Kroner, F.K., 1995. Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11, 122-150.

Granger, C.W.J., 1969, Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37(3), 424-438.

Groen, J.J., 2000. The Monetary Exchange Rate Model as a Long-Run Phenomenon. *Journal of International Economics* 52, 299–319.

Hiemstra, C. and Jones, J.D., 1994. Testing for linear and nonlinear Granger causality in the stock price-volume relation. *Journal of Finance* 49(5), 1639-1664.

Johansen, S., 1988. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control* 12(2-3), 231–254.

Johansen, S. and Juselius, K., 1990. Maximum likelihood estimation and inference on cointegration with application to the demand for money. *Oxford Bulletin of Economics and Statistics* 52, 169–209.

Johansen, S., 1991. Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. *Econometrica* 59, 1551–1580.

Hsieh, D., 1989. Modeling heteroscedasticity in daily foreign exchange rates. *Journal of Business and Economic Statistics* 7, 307–317.

Kilian, L. and Taylor, M.P., 2003. Why Is It So Difficult to Beat the Random Walk Forecast of Exchange Rates?. *Journal of International Economics* 60, 85–107.

MacDonald, R. and Taylor, M.P., 1994. The Monetary Model of the Exchange Rate: Long-Run Relationships, Short-Run Dynamics and How to Beat a Random Walk. *Journal of International Money and Finance* 13 276–290.

Mark, N.C. 1995. Exchange Rates and Fundamentals: Evidence on Long- Horizon Predictability. *American Economic Review* 85, 201–218.

Mark, N.C., and Sul, D., 2001. Nominal Exchange Rates and Monetary Fundamentals: Evidence from a Small Post–Bretton Woods Sample. *Journal of International Economics* 53, 29–52.

Meese, R.A. and Rogoff, K.S., 1983a. Empirical Exchange Rate Models of the Seventies: Do They Fit Out of Sample?. *Journal of International Economics* 14, 3–24.

Meese, R.A. and Rogoff, K.S., 1983b. The Out of Sample Failure of Empirical Exchange Models. In: Exchange Rates and International Macroeconomics, (Eds) J. A. Frenkel. Chicago: Univ. Chicago Press.

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

West, K.D., 1988. Dividend Innovations and Stock Price Volatility. *Econometrica* 56, 37–61.

TABLE 1: AUTOCORRELATIONS AND CROSS-CORRELATIONS OF FX AND FUNDAMENTALS (MEAN)

			Correlation of Δs_t with					
b	ϕ_1	ϕ	Δs_{t-1}	Δs_{t-2}	Δs_{t-3}	Δx_{t-1}	Δx_{t-2}	Δx_{t-3}
0.5	1.0	0.3	0.11	0.08	0.03	0.13	0.08	0.06
		0.5	0.32	0.20	0.12	0.38	0.18	0.13
		0.8	0.45	0.39	0.32	0.50	0.43	0.40
0.9	1.0	0.3	0.01	0.00	0.00	0.02	0.01	0.00
		0.5	0.02	0.01	0.01	0.04	0.02	0.01
		0.8	0.03	0.02	0.02	0.08	0.06	0.05
0.95	1.0	0.3	0.00	0.00	-0.00	0.01	0.00	0.00
		0.5	-0.00	0.01	0.00	0.01	0.01	0.00
		0.8	-0.02	0.02	0.01	0.05	0.03	0.02
0.9	0.9	0.5	-0.00	-0.02	-0.02	-0.01	-0.04	-0.05
0.9	0.95	0.5	-0.00	0.00	-0.01	0.00	-0.02	-0.02
0.95	0.95	0.5	0.00	-0.00	-0.01	-0.00	-0.01	-0.02
0.95	0.99	0.5	-0.00	0.00	-0.00	0.00	0.00	-0.00

Notation: The model is $s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t x_{t+j}$ or $s_t = b\sum_{j=0}^{\infty} b^j E_t x_{t+j}$. The scalar variable x_t follows an $\mathrm{AR}(2)$ process with autoregressive roots φ_1 and φ. When $\varphi_1 = 1.0$, $\Delta x_t \sim \mathrm{AR}(1)$ with parameter φ. If $\varphi_1 = 1.0$, as in rows 1–9, then in the limit, as $b \to 1$, each of these correlations approaches zero. The setup of the simulations is the following: x_t=1500 observations are produced with j=5000 forward steps to the future. Thus in total a path of 6500 observations is generated. Next, the first burn-out 500 points are discarded. Therefore the examined processes for x_t (fundamental), s_t (currency) and z_t (another currency series) include 1000 observations. Then correlations are computed, the paths are replicated 2000 times and the mean, median and mode of the correlations are estimated.

TABLE 2: AUTOCORRELATIONS AND CROSS-CORRELATIONS OF FX AND FUNDAMENTALS (MEDIAN)

			Correlation of Δs_t with					
b	ϕ_1	ϕ	Δs_{t-1}	Δs_{t-2}	Δs_{t-3}	Δx_{t-1}	Δx_{t-2}	Δx_{t-3}
0.5	1.0	0.3	0.09	0.06	0.05	0.11	0.07	0.05
		0.5	0.30	0.22	0.10	0.35	0.16	0.12
		0.8	0.42	0.35	0.31	0.48	0.41	0.39
0.9	1.0	0.3	0.01	0.00	-0.00	0.02	0.01	-0.00
		0.5	0.02	0.00	0.00	0.05	0.02	0.02
		0.8	0.03	0.03	0.02	0.09	0.07	0.04
0.95	1.0	0.3	-0.00	-0.00	0.00	0.01	-0.00	-0.00
		0.5	0.01	0.01	0.00	0.01	0.01	0.00
		0.8	-0.02	0.02	0.01	0.04	0.03	0.02
0.9	0.9	0.5	0.00	-0.02	-0.03	-0.02	-0.04	-0.05
0.9	0.95	0.5	0.00	-0.00	-0.00	0.00	-0.02	-0.02
0.95	0.95	0.5	-0.00	-0.00	-0.01	-0.01	-0.02	-0.02
0.95	0.99	0.5	-0.01	0.00	-0.00	0.00	-0.00	-0.00

Notation: Same as in Table 1

TABLE 3: AUTOCORRELATIONS AND CROSS-CORRELATIONS OF FX AND FUNDAMENTALS (MODE)

			Correlation of Δs_t with					
b	ϕ_1	ϕ	Δs_{t-1}	Δs_{t-2}	Δs_{t-3}	Δx_{t-1}	Δx_{t-2}	Δx_{t-3}
0.5	1.0	0.3	0.09	0.04	0.03	0.11	0.05	0.02
		0.5	0.29	0.20	0.11	0.32	0.15	0.10
		0.8	0.42	0.33	0.30	0.44	0.39	0.37
0.9	1.0	0.3	0.01	0.00	0.00	0.02	0.01	0.00
		0.5	0.02	-0.00	0.01	0.04	0.02	0.01
		0.8	0.03	0.02	0.02	0.09	0.07	0.05
0.95	1.0	0.3	-0.00	0.00	0.00	0.00	-0.00	0.00
		0.5	0.00	0.00	0.00	0.01	0.00	0.00
		0.8	-0.02	0.01	0.01	0.04	0.03	0.02
0.9	0.9	0.5	-0.00	-0.02	-0.02	-0.01	-0.04	-0.05
0.9	0.95	0.5	0.00	0.00	-0.00	0.00	-0.01	-0.02
0.95	0.95	0.5	-0.00	-0.00	-0.02	-0.00	-0.01	-0.02
0.95	0.99	0.5	-0.01	0.00	-0.00	0.00	0.00	-0.00

Notation: Same as in Table 1

TABLE 4: CAUSALITY AND CROSS-CORRELATION OF THE SIMULATED FX AND FUNDAMENTALS SERIES

Granger-causality on the Raw series

b	ϕ_1	ϕ	*GC: s->x*		*GC: x->s*		*CI (s,x)*
			0.95	0.99	0.95	0.99	
0.5	1.0	0.3	5.9%	1.75%	62.2%	40.5%	100%
		0.5	4.8%	1.1%	68%	57%	100%
		0.8	5.3%	1.1%	88.7%	77.8%	100%
0.95	1.0	0.3	4.75%	1.2%	18%	12.2%	98.5%
		0.5	3.8%	1%	29%	23%	97.1%
		0.8	4.8%	0.95%	38.8%	28.7%	97.2%

Correlation on the Filtered series

b	ϕ_1	ϕ	*Correlation (s,x)*			
0.5	1.0	0.3	Mode	Median	Mean	St.Err
		Raw data	0.93	0.93	0.93	0.00
		VECM/VAR filtering	0.96	0.96	0.96	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.3	Mode	Median	Mean	St.Err
		Raw data	0.84	0.84	0.84	0.00
		VECM/VAR filtering	0.93	0.92	0.91	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	Correlation (s,x)			
			Mode	Median	Mean	St.Err
0.5	1.0	0.5				
		Raw data	0.90	0.89	0.88	0.00
		VECM/VAR filtering	0.97	0.97	0.97	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.5	Mode	Median	Mean	St.Err
		Raw data	0.72	0.72	0.72	0.00
		VECM/VAR filtering	0.87	0.89	0.89	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	Correlation (s,x)			
			Mode	Median	Mean	St.Err
0.5	1.0	0.8				
		Raw data	0.83	0.83	0.83	0.00
		VECM/VAR filtering	0.96	0.96	0.96	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.8	Mode	Median	Mean	St.Err
		Raw data	0.45	0.46	0.46	0.00
		VECM/VAR filtering	0.74	0.71	0.72	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

Notation: The model is $s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t x_{t+j}$ or $s_t = b\sum_{j=0}^{\infty} b^j E_t x_{t+j}$. The scalar variable x_t follows an $\mathrm{AR}(2)$ process with autoregressive roots φ_1 and φ. When $\varphi_1 = 1.0$, $\Delta x_t \sim \mathrm{AR}(1)$ with parameter φ. If $\varphi_1 = 1.0$, as in rows 1–9, then in the limit, as $b \to 1$, each of these correlations approaches zero. The setup of the simulations is the following: x_t=1500 observations are produced with j=5000 forward steps to the future. Thus in total a path of 6500 observations is generated. Next, the first burn-out 500 points are discarded. Therefore the examined processes for x_t (fundamental), s_t (currency) and z_t (another currency series) include 1000 observations. Then correlations are computed, the paths are replicated 2000 times and the mean, median and mode of the correlations are estimated. Granger causality (GC) is investigated via a VAR or VECM representation depending on the whether the Johansen trace statistic rejects the null of no cointegration (CI) or not for each pair of the examined simulated paths. The numbers presented for GC are the percentages of the Granger-caused series detected. Next, the GARCH-BEKK is applied for second-moment filtering.

TABLE 5: CAUSALITY AND CROSS-CORRELATION OF TWO DIFFERENT SIMULATED FX SERIES

Granger-causality on the Raw series

b	ϕ_1	ϕ	*GC: s->z*		*GC: z->s*		*CI (s,z)*
			0.95	0.99	0.95	0.99	
0.5	1.0	0.3	8.5%	2.2%	9.95%	2.4%	20%
		0.5	8.3%	1.4%	9.7%	2.1%	14.3%
		0.8	9.7%	2.5%	9.8%	2.4%	22.3%
0.95	1.0	0.3	7.95%	1.65%	7.6%	1.35%	18.2%
		0.5	9.5%	2.2%	7.75%	2.1%	13.5%
		0.8	9.4%	2.35%	9.85%	2.45%	25.15%

Correlation on the Filtered series

b	ϕ_1	ϕ	*Correlation (s,z)*			
			Mode	Median	Mean	St.Err
0.5	1.0	0.3				
		Raw data	0.00	-0.00	-0.00	0.00
		VECM/VAR filtering	0.00	-0.00	-0.00	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.3	Mode	Median	Mean	St.Err
		Raw data	-0.00	-0.00	-0.00	0.00
		VECM/VAR filtering	-0.00	-0.00	-0.00	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	*Correlation (s,z)*			
			Mode	Median	Mean	St.Err
0.5	1.0	0.5				
		Raw data	-0.00	-0.00	0.00	0.00
		VECM/VAR filtering	-0.00	0.00	-0.00	0.00
		GARCH filtering	0.00	-0.00	0.00	0.00
0.95	1.0	0.5	Mode	Median	Mean	St.Err
		Raw data	0.00	0.00	0.00	0.00
		VECM/VAR filtering	0.00	0.00	0.00	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	*Correlation (s,z)*			
			Mode	Median	Mean	St.Err
0.5	1.0	0.8				
		Raw data	0.00	0.00	0.00	0.00
		VECM/VAR filtering	0.00	0.00	0.00	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.8	Mode	Median	Mean	St.Err
		Raw data	0.00	0.00	0.00	0.00
		VECM/VAR filtering	0.00	0.00	0.00	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

Notation: Same as in Table 4

TABLE 6: CAUSALITY AND CROSS-CORRELATION OF TWO DIFFERENT SIMULATED FX SERIES WITH THE SAME FUNDAMENTALS DRIVER

Granger-causality on the Raw series

b	ϕ_1	ϕ	*GC: s->z_2*		*GC: z_2->s*		*CI (s,z_2)*
			0.95	0.99	0.95	0.99	
0.5	1.0	0.3	23.25%	15.25%	25.35%	15.05%	100%
		0.5	24.4%	26.5%	23%	25.1%	100%
		0.8	26.4%	19.3%	26.1%	18.8%	100%
0.95	1.0	0.3	12.05%	6.3%	11.5%	7.2%	100%
		0.5	8.9%	3.7%	8.25%	3.6%	100%
		0.8	9.3%	7.21%	12.8%	7.3%	100%

Correlation on the Filtered series

b	ϕ_1	ϕ	*Correlation (s,z_2)*			
0.5	1.0	0.3	Mode	Median	Mean	St.Err
		Raw data	0.93	0.93	0.93	0.00
		VECM/VAR filtering	0.95	0.95	0.96	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.3	Mode	Median	Mean	St.Err
		Raw data	0.78	0.78	0.78	0.00
		VECM/VAR filtering	0.85	0.85	0.86	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	*Correlation* (s, z_2)			
			Mode	Median	Mean	St.Err
0.5	1.0	0.5				
		Raw data	0.93	0.93	0.94	0.00
		VECM/VAR filtering	0.96	0.96	0.96	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.5	Mode	Median	Mean	St.Err
		Raw data	0.69	0.68	0.68	0.00
		VECM/VAR filtering	0.80	0.80	0.78	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

b	ϕ_1	ϕ	*Correlation* (s, z_2)			
			Mode	Median	Mean	St.Err
0.5	1.0	0.8				
		Raw data	0.95	0.95	0.95	0.00
		VECM/VAR filtering	0.97	0.96	0.96	0.00
		GARCH filtering	0.00	0.00	0.00	0.00
0.95	1.0	0.8	Mode	Median	Mean	St.Err
		Raw data	0.61	0.61	0.61	0.00
		VECM/VAR filtering	0.71	0.70	0.69	0.00
		GARCH filtering	0.00	0.00	0.00	0.00

Notation: Same as in Table 4

TABLE 7: PREDICTABILITY OF DIFFERENT FX AND FUNDAMENTALS DATA GENERATING PROCESSES

b	ϕ_1	ϕ	Mode	Median	Mean	St.Err	Mode	Median	Mean	St.Err	Mode	Median	Mean	St.Err
			R1 (RMSE1/RMSE2)				R2 (RMSE1/RMSE3)				R3 (RMSE1/RMSE4)			
0.5	1.0	0.3	0.98	0.98	0.97	0.00	0.10	0.09	0.14	0.00	0.99	0.99	1.00	0.00
		0.5	0.98	0.97	0.96	0.00	0.11	0.09	0.15	0.00	1.00	1.00	0.99	0.00
		0.8	0.99	0.99	0.98	0.00	0.11	0.10	0.16	0.00	1.00	1.00	1.00	0.00
0.95	1.0	0.3	0.99	0.99	0.98	0.00	0.19	0.15	0.15	0.00	0.99	0.99	1.00	0.00
		0.5	0.99	0.99	0.98	0.00	0.21	0.15	0.15	0.00	1.00	1.00	1.00	0.00
		0.8	0.99	1.00	0.99	0.00	0.21	0.19	0.16	0.00	1.00	1.00	1.01	0.00

b	ϕ_1	ϕ	Mode	Median	Mean	St.Err	Mode	Median	Mean	St.Err
			R4 (RMSE1/RMSE5)				R5 (RMSE1/RMSE6)			
0.5	1.0	0.3	0.96	0.97	0.97	0.00	0.99	1.00	1.00	0.00
		0.5	0.97	0.97	0.97	0.00	1.00	1.00	1.00	0.00
		0.8	0.98	0.97	0.97	0.00	1.06	1.06	1.07	0.00
0.95	1.0	0.3	0.98	0.99	1.00	0.00	1.01	1.01	1.01	0.00
		0.5	0.98	0.98	1.00	0.00	1.02	1.02	1.02	0.00
		0.8	0.98	0.98	0.99	0.00	1.02	1.02	1.03	0.00

Notation: Various data generating processes are produced by the simulations. Specifically, four $\mathrm{AR}(1)$ specifications are used with the lagged variable being the FX series, the fundamentals series, the FX series with the same and different fundamental driver, i.e., (1) $s_t = \beta s_{t-1} + \varepsilon_t$, (2) $s_t = \gamma x_{t-1} + \varepsilon_t$, (3) $s_t = \delta z_{t-1} + \varepsilon_t$ (with different fundamentals driver), (4) $s_t = \zeta z_{t-1} + \varepsilon_t$ (with same fundamentals driver). Also two $\mathrm{AR}(1)$ specifications are used employing both a lagged fundamental and an FX series with the same and different fundamental driver, i.e., (5) $s_t = \beta_1 x_{t-1} + \beta_2 z_{t-1} + \varepsilon_t$ (with different fundamentals driver) and (6) $s_t = \gamma_1 x_{t-1} + \gamma_2 z_{t-1} + \varepsilon_t$ (with same fundamentals driver). The out-of-sample measure is the RMSE and in particular the RMSE ratios are reported against the first $\mathrm{AR}(1)$ model which is used as a benchmark. The simulated series again correspond to rows 1-3 and 7-9 of Tables 1-3, that is with $b = 0.5$ and $b = 0.95$. Also, the mode, mean and median is reported.

TABLE 8: LINEAR CAUSALITY (PAIRWISE)

Panel A: Linear Granger Causality — Raw data

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(m-m*)*										*		*		*
Δs	*Δ(p-p*)*														
Δs	*i-i**				*										*
Δs	*Δ(i-i*)*				*										
Δs	*Δ(y-y*)*			*		**							*		
Δs	*Δ(m-m*) - Δ(y-y*)*					**					*		**		

Panel A: Linear Granger Causality — VAR / VECM residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(m-m*)*														
Δs	*Δ(p-p*)*														
Δs	*i-i**														
Δs	*Δ(i-i*)*														
Δs	*Δ(y-y*)*														
Δs	*Δ(m-m*) - Δ(y-y*)*														

Panel A: Linear Granger Causality — GARCH-BEKK residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(m-m*)*														
Δs	*Δ(p-p*)*														
Δs	*i-i**														
Δs	*Δ(i-i*)*														
Δs	*Δ(y-y*)*														
Δs	*Δ(m-m*) - Δ(y-y*)*														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

All data (levels) were investigated with a VECM specification and the null of no cointegration was not rejected for all except *DM: Δs-Δ(p-p*), AUD: Δs-Δ(i-i*), JPY: Δs-Δ(i-i*), EUR: Δs-Δ(i-i*)*. The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors)*. VAR(1,0) is identified except VAR(2,0) in *GBP: Δs-Δ(m-m*), GBP: Δs-Δ(m-m*), DM: Δs-(i-i*)*. VECM (2,1) is identified in all cointegrated pairs except *AUD: Δs-Δ(i-i*)*, which is VECM(1,1). For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 9: NONLINEAR CAUSALITY (PAIRWISE)

Panel B: NonLinear Causality — Raw data

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	Δ(m-m*)	*													
Δs	Δ(p-p*)														
Δs	i-i*	*	*						**		*				
Δs	Δ(i-i*)	*	*				*		*						
Δs	Δ(y-y*)								*		*				
Δs	Δ(m-m*) - Δ(y-y*)														

Panel B: NonLinear Causality — VAR / VECM residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	Δ(m-m*)	*													
Δs	Δ(p-p*)														
Δs	i-i*	*	*						*						
Δs	Δ(i-i*)	*	*				*		*						
Δs	Δ(y-y*)										*				
Δs	Δ(m-m*) - Δ(y-y*)														

Panel B: NonLinear Causality — GARCH-BEKK residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	Δ(m-m*)	*													
Δs	Δ(p-p*)														
Δs	i-i*														
Δs	Δ(i-i*)														
Δs	Δ(y-y*)										*				
Δs	Δ(m-m*) - Δ(y-y*)														

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 10: LINEAR CAUSALITY (5X5)

Panel A: Linear Granger Causality — Raw data

Variable		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	Δ(m-m*)											*	*		*
Δs	Δ(p-p*)									**					
Δs	Δ(i-i*)														
Δs	Δ(y-y*)					**			*		*		*		

Panel A: Linear Granger Causality — VAR / VECM residuals

Variable		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	Δ(m-m*)														
Δs	Δ(p-p*)														
Δs	Δ(i-i*)														
Δs	Δ(y-y*)														

Panel A: Linear Granger Causality — GARCH-BEKK residuals

Variable		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	Δ(m-m*)														
Δs	Δ(p-p*)														
Δs	Δ(i-i*)														
Δs	Δ(y-y*)														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

The 5x5 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all except *EUR.* The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(5,1), JPY(4,1), CHF(8,1), AUD(3,1), CAD(4,1), DM(2,2), EUR(1,0).* For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 11: NONLINEAR CAUSALITY (5X5)

Panel B: NonLinear Causality — Raw data

X	Y	X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(m-m*)*	*													
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*	*	*				*		*						
Δs	*Δ(y-y*)*								*		*				

Panel B: NonLinear Causality — VAR / VECM residuals

X	Y	X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(m-m*)*														
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*	*					*		*						
Δs	*Δ(y-y*)*														

Panel B: NonLinear Causality — GARCH-BEKK residuals

X	Y	X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(m-m*)*														
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*														
Δs	*Δ(y-y*)*														

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 12: LINEAR CAUSALITY (4X4)

Variable		Panel A: Linear Granger Causality													
		Raw data													
		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*				*										
Δs	*Δ(y-y*)*					**							*		

Variable		VAR / VECM residuals													
		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*														
Δs	*Δ(y-y*)*														

Variable		GARCH-BEKK residuals													
		X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(i-i*)*														
Δs	*Δ(y-y*)*														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**).*The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

The 4x4 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all except *GBP, JPY, AUD and CAD.* The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(1,0), JPY(1,0), CHF(5,1), AUD(1,0), CAD(1,0), DM(2,2), EUR(2,1).* For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 13: NONLINEAR CAUSALITY (4X4)

Variable		**Panel B: NonLinear Causality**																																									
		Raw data														**VAR / VECM residuals**														**GARCH-BEKK residuals**													
X	**Y**	X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*																																										
Δs	*Δ(i-i*)*	*	*				*		*							*	*				*		*												*								
Δs	*Δ(y-y*)*								*		*																																

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 14: LINEAR CAUSALITY (4X4)

Variable		Panel A: Linear Granger Causality																																									
		Raw data														VAR / VECM residuals														GARCH-BEKK residuals													
X	Y	X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	$\Delta(m-m^*)$																																										
Δs	$\Delta(p-p^*)$																																										
Δs	$\Delta(y-y^*)$					**			*				*																														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

The 4x4 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all except *AUD and EUR.* The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(5,2), JPY(4,1), CHF(2,1), AUD(2,0), CAD(4,1), DM(2,1), EUR(1,0).* For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 15: NONLINEAR CAUSALITY (4X4)

Variable		Panel B: NonLinear Causality																																									
		Raw data														VAR / VECM residuals														GARCH-BEKK residuals													
X	Y	X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(m-m*)*	*																																									
Δs	*Δ(p-p*)*																																										
Δs	*Δ(y-y*)*								*		*														*														*				

<u>Panel B: Non-Linear Causality</u>

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 16: LINEAR CAUSALITY (4X4)

Panel A: Linear Granger Causality — Raw data

Variable X	Variable Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**				*										
Δs	*Δ(y-y*)*					**							*		

Panel A: Linear Granger Causality — VAR residuals

Variable X	Variable Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**														
Δs	*Δ(y-y*)*														

Panel A: Linear Granger Causality — GARCH-BEKK residuals

Variable X	Variable Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**														
Δs	*Δ(y-y*)*														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

The 4x4 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all. The lag lengths of VAR specification are investigated and set using the SIC and Wald exclusion criterion. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(1,0), JPY(1,0), CHF(1,0), AUD(1,0), CAD(1,0), DM(1,0), EUR(2,0).* For testing reasons Linear Granger causality was further investigated in the VAR or GARCH residuals, but not detected.

TABLE 17: NONLINEAR CAUSALITY (4X4)

Panel B: NonLinear Causality — Raw data

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**	*	*						*						
Δs	*Δ(y-y*)*														

Panel B: NonLinear Causality — VAR / VECM residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**	*	*						*						
Δs	*Δ(y-y*)*														

Panel B: NonLinear Causality — GARCH-BEKK residuals

X	Y	X→Y GBP	X→Y JPY	X→Y CHF	X→Y AUD	X→Y CAD	X→Y DM	X→Y EUR	Y→X GBP	Y→X JPY	Y→X CHF	Y→X AUD	Y→X CAD	Y→X DM	Y→X EUR
Δs	*Δ(p-p*)*														
Δs	*i-i**		*												
Δs	*Δ(y-y*)*														

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 18: LINEAR CAUSALITY (3X3)

Variable		Panel A: Linear Granger Causality																																									
		Raw data														VAR / VECM residuals														GARCH-BEKK residuals													
		X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
X	**Y**	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	$\Delta(p-p^*)$																																										
Δs	$\Delta(y-y^*)$					**			**				*																														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

<u>Panel A: Linear Granger Causality</u>
The 3x3 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all except *JPY, CHF, AUD, CAD, EUR*. The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(2,1), JPY(1,0), CHF(1,0), AUD(1,0), CAD(1,0), DM(2,1), EUR(1,0)*. For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 19: NONLINEAR CAUSALITY (3X3)

Panel B: NonLinear Causality — Raw data

Variable		X→Y							Y→X						
X	**Y**	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(y-y*)*								*		*				

Panel B: NonLinear Causality — VAR / VECM residuals

Variable		X→Y							Y→X						
X	**Y**	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(y-y*)*										*				

Panel B: NonLinear Causality — GARCH-BEKK residuals

Variable		X→Y							Y→X						
X	**Y**	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(p-p*)*														
Δs	*Δ(y-y*)*														

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

TABLE 20: LINEAR CAUSALITY (3X3)

Variable		Panel A: Linear Granger Causality																																									
X	Y	Raw data														VAR / VECM residuals														GARCH-BEKK residuals													
		X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
		GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	$\Delta(m-m^*)$												*																														
Δs	$\Delta(y-y^*)$					**							*																														

X→Y: r_X does not Granger Cause r_Y. Statistical significance *5% (*), 1% (**)*.The foreign exchange rates are Euro (EUR), Great Britain Pound (GBP), Japanese Yen (JPY), Swiss Frank (CHF), Australian Dollar (AUD), Canadian Dollar (CAD) and German mark (DM) are denoted relative to United States dollar (USD). The exact ratios represent EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD and DM/USD respectively. The *FX rates* are denoted as *s* and fundamentals as: *m=Money, p=CPI, i=Interest rate, y=IP, m-y=Money- IP*. In differentials *(*)* denotes non-US value. Causalities are investigated on *Δ(differentials)*. All data but interest rates are converted by taking logs and multiplying by 100. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

Panel A: Linear Granger Causality

The 3x3 system of the data (levels) for each FX was investigated with a VECM specification and the null of no cointegration was rejected for all except *GBP, AUD, CAD, DM.* The lag lengths of VECM/VAR specification are investigated and set using the SIC and Wald exclusion criterion and the cointegrating vectors using the Johansen trace statistic. The number of lags identified and the cointegrating vectors are presented in parenthesis as *(lags, coint. vectors): GBP(1,0), JPY(2,1), CHF(2,1), AUD(1,0), CAD(1,0), DM(1,0), EUR(2,1).* For testing reasons Linear Granger causality was further investigated in the VAR/VECM or GARCH residuals, but not detected.

TABLE 21: NONLINEAR CAUSALITY (3X3)

Variable		Panel B: NonLinear Causality																																									
		Raw data														VAR / VECM residuals														GARCH-BEKK residuals													
		X→Y							Y→X							X→Y							Y→X							X→Y							Y→X						
X	Y	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR	GBP	JPY	CHF	AUD	CAD	DM	EUR
Δs	*Δ(m-m*)*	*																																									
Δs	*Δ(y-y*)*								*		*														*														*				

Panel B: Non-Linear Causality

The number of lags used for the nonlinear causality test are $\ell_X = \ell_Y = 1$. The data used are log-returns. The nonlinear causality was investigated on the VAR/VECM residuals based on Panel A System identification. The number of lags and cointegrating vectors are reported in Panel A. The second moment filtering was performed with a GARCH-BEKK (1,1) model. The Chow-Lin method was used to interpolate AUD^{CPI}, AUD^{IP}, CHF^{IP} and backdate JPY^{i}. *Total period (levels): 4/1986 – 7/2008. EURO period (levels): 1/1999 – 7/2008.*

European University Institute
European University Press