"The US Dollar-Euro exchange rate and US-EMU bond yield differentials: A Causality Analysis"

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Abstract

This paper test for causality between the US Dollar-Euro exchange rate and US-EMU bond yield differentials. To that end, we apply Hsiao (1981)'s sequential procedure to daily data covering January 1999- January 2011 period. Our results suggest the existence of statistically significant Granger causality running one-way from bond yield differentials to the exchange rate, but not the other way around.

Keywords: Causality, Exchange rate, Long-term interest rates, Rolling regression

JEL Codes: C32, F33, G12, G13

1. Introduction

Since the beginning of the European Economic and Monetary Union (EMU), the US dollar-Euro exchange rate has fluctuated considerably. The ups and downs of the exchange rate have coincided with varying interest rate differentials between the USA and EMU.

Interest rates have long been considered key determinants of exchange rate movements despite empirical failure of the uncovered interest rate parity (UIP) (see Engle, 1996, for a survey). Nevertheless, in the majority of cases, tests of UIP have been based on short-run interest rates. In recent years, there is growing evidence supporting a relatively robust fundamental relationship between long-term interest rates and exchange rates [see, for example, Flood and Taylor (1996), Alexius (2001), and Chinn and Meredith (2004)].

The diverging results could be related to the fact that movements in short-term interest rates are largely a reflection of the impact of monetary policy measures, whereas changes in long-term interest rates also reflect long-term growth and inflation expectations.

The aim of this paper is to provide some additional evidence on the relationship between interest rates and exchange rate. To that end, we apply time series techniques to determine the appropriate Granger relations between nominal long-term interest rates and the nominal exchange rate using EMU data. Via Hsiao (1981)'s sequential procedure, it is found that the long-term interest rate differential between USA and EMU Granger causes the US dollar-Euro exchange rate, but not the other way around.

This paper is laid out as follows. Section 2 explains our econometric methodology. Section 3 considers the data used in this study, and presents and interprets our empirical results. Section 4 reports results from rolling regression to assess the model's stability over time. This paper ends with Section 5 that summarizes our findings.

2. Econometric methodology

Granger (1969)'s causality test is widely used to test for the relationship between two variables. However, the causality tests are sensitive to lag length and, therefore, it is important to select the appropriate lengths. Otherwise, the model estimates will be inconsistent and, therefore, it is likely we draw misleading inferences (see, Thornton and Batten, 1985). In this paper, we use Hsiao's (1981) generalization of the Granger notion of causality. He proposed a sequential method to test for causality, which combines the Akaike (1969)'s final predictive error (FPE, from now on) and the definition of Granger causality. Essentially, the FPE criterion trades off bias that arises from under parametrization of a model against a loss in efficiency that results from over parameterization of the model.

Consider the following models,

$$X_t = \alpha_0 + \sum_{i=1}^{m} \delta_i X_{t-i} + \varepsilon_t \qquad (1)$$

$$X_t = \alpha_0 + \sum_{i=1}^{m} \delta_i X_{t-i} + \sum_{j=1}^{n} \gamma_j Y_{t-j} + \varepsilon_t \qquad (2)$$

where X_t and Y_t are stationary variables [i.e., they are I(0) variables]. The following steps are used to apply Hsiao's procedure for testing causality:

(i) Treat X_t as a one-dimensional autoregressive process (1), and compute its FPE with the order of lags *m* varying from 1 to *m*[1]. Choose the order which yields the smallest FPE, say *m*, and denote the corresponding FPE as FPE_X (m, 0).

(ii) Treat X_t as a controlled variable with *m* number of lags, and treat Y_t as a manipulated variable as in (2). Compute again the FPE of (2) by varying the order of lags of Y_t from 1 to *n*, and determine the order which gives the smallest FPE, say *n*, and denote the corresponding FPE as FPE_X (m,n) [2].

(iii) Compare FPE_X (m, 0) with FPE_X(m,n) [i.e., compare the smallest FPE in step (i) with the smallest FPE in step (ii)]. If FPE_X (m,0) > FPE_X (m,n), then Y_t is said to cause X_t. If FPE_X (m,0) < FPE_X (m,n), then X_t is an independent process.

(iv) Repeat steps (i) to (iii) for the Y_t variable, treating X_t as the manipulated variable.

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[1] FPE_X(m,0) is computed using the formula: $FPE_X(m,0) = \frac{T+m+1}{T-m-1} \cdot \frac{SSR}{T}$, where T is the total number of observations and SSR is the sum of squared residuals of OLS regression (1)

[2] FPE_X(m,n) is computed using the formula: $FPE_X(m,n) = \frac{T+m+n+1}{T-m-n-1} \cdot \frac{SSR}{T}$, where T is the total number of observations and SSR is the sum of squared residuals of OLS regression (2)

When X_t and Y_t are not stationary variables, but they are first-difference stationary [i.e., they are I(1) variables] and they are cointegrated (see Dolado et al., 1990), it is possible to investigate the causal relationships from ΔX_t to ΔY_t and from ΔY_t to ΔY_t, using the following error correction models:

$$\Delta X_t = \alpha_0 + \beta Z_{t-1} + \sum_{i=1}^{m} \delta_i \Delta X_{t-i} + \varepsilon_t \qquad (3)$$

$$\Delta X_t = \alpha_0 + \beta Z_{t-1} + \sum_{i=1}^{m} \delta_i \Delta X_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta Y_{t-j} + \varepsilon_t \qquad (4)$$

where Z_t is the OLS residual of the cointegrating regression $X_t = \mu + \lambda Y_t$. Note that, if X_t and Y_t are I (1) variables, but they are not cointegrated, then β in (3) and (4) is assumed to be equal to zero.

In both cases [i.e., X_t and Y_t are I(1) variables, and they are or they are not cointegrated], we can use Hsiao's sequential procedure substituting X_t with ΔX_t and Y_t with ΔY_t in steps (i) to (iv), as well as substituting expressions (1) and (2) with equations (3) and (4).

3. Data and empirical results

3.1. Data

We use daily data of US dollar-Euro exchange rate taking from the European Central Bank´s Statistical Data Warehouse. Regarding the US long-run interest rate, we use ten-year Treasury Constant Maturity Rate taking from the Board of Governors of the Federal Reserve System. As for the EMU long-term interest rates, we use as a proxy the JPM EMU Government Bond Index taking from the JPM EMU Bonds Index, FAKING FROM J.P. Morgan. Our database covers the period January 1999 to January 2011.

To avoid using index and row data, we construct indices for both the US dollar-Euro exchange rate and the US long-run interest rates using the same base year than the JPM EMU Government Bond Index. Once these indices are constructed, we compute the long-run interest rate differentials between the USA and EMU.

3.2. Preliminary results

As a first step, we tested for the order of integration of the US dollar-Euro exchange rate (that we denote S) and the USA-EMU long-term interest rate differential (that we denote DIF) by means of the Augmented Dickey-Fuller (ADF) tests. The results, shown in Table 1, decisively reject the null hypothesis of nonstationarity, suggesting that both variables could be treated as first-difference stationary.

[Insert Table 1 here]

Following Carrion-i-Silvestre *et al.* (2001)´s suggestion, we confirm this result using the Kwiatkowski *et al.* (1992) (KPSS) tests, where the null is a stationary process against the alternative of a unit root. As can be seen in Table 2, the results fail to reject the null hypothesis of stationarity in first-difference but strongly reject it in levels.

[Insert Table 2 here]

As a second step, we have tested for cointegration between exchange rate and the long-term interest rate differential. To that end, we use the Johansen (1991, 1995) cointegration test. As can be seen in Table 3, the trace tests indicate no cointegration.

[Insert Table 3 here]

3. 3. Causality results

While the results from the cointegration tests deny a long-run relationship between the exchange rate and the long-term interest rate differential, they do not rule out the possibility of a short-run relationship. Therefore, we tested for causality in first differences of the variables, with no error-correction term added [i. e., equations (3) and (4), with $\beta = 0$. Table 4 shows the optimum order of lags and the corresponding FPEs. The reported F-statistics are the Wald statistics to test the joint hypothesis $\hat{\gamma}_1 = \hat{\gamma}_2 = ... = \hat{\gamma}_n = 0$.

[Insert Table 4 here]

As can be seen, the optimum order lag m of ΔS_{t-j} (ΔDIF_{t-j}) when ΔS_t (ΔDIF_t) is regressed on its own past values and a constant only is one (two), while the optimum order lag n of ΔDIF_{t-j} (ΔS_{t-j}) when ΔS_t (ΔDIF_t) is regressed on its own past values (whose order of lags is fixed at m), the past values of ΔDIF_{t-j} (ΔS_{t-j}) and a constant is three (one). On the other hand, $FPE_{\Delta S}(m, 0) > FPE_{\Delta S}(m, n)$ and $FPE_{\Delta DIF}(m, 0) < FPE_{\Delta DIF}(m, n)$, suggesting that Granger causality runs one-way from DIF to S and not the other way. This conclusion is also reached using the F-statistics since it is significant at the 1 percent level when testing that all coefficients of the lagged ΔS_t are zeros, but we cannot reject the null hypothesis that all coefficients of the lagged ΔDIF_t are zeros at the usual levels.

In order to further check our results, we have computed the Williams-Kloot test for forecasting accuracy described in Williams (1959). Let f_1 and $f2$ denote alternative forecasts of the variable z, the Williams-Kloot test statistic is the t-ratio for the hypothesis that the coefficient on $f_1 - f_2$ is zero in a regression of $z - (f_1 + f_2)/2$ on $f_1 - f2$. A significantly negative value implies that f_2 is statistically superior to that of $f1$ (and *vice versa*). Therefore, we generated forecasts for ΔS and ΔDIF both considering only past values of the forecasted variable and considering also, in addition, past values of the other variable. The results are shown in Table 5. As can be seen, the Williams-Kloot test suggests that ΔS_t can be better predicted by adding the information content of the ΔDIF_t, rather than by past values of ΔS_{t-j} alone. On the other hand, forecasting accuracy for ΔDIF_t cannot be gained by considering also the information content of ΔS_{t-j}. Therefore, these results reinforce our earlier conclusion about from Table 4.

[Insert Table 5 here]

4. Rolling regressions

In this section, we make use of rolling analysis to check for changes in causality between the US dollar-Euro exchange rate and the USA-EMU long-term interest rate differential over time. Specifically, we report the results of estimates from a sequence of short rolling samples to track a possibly evolving relationship in the sense of time-varying. The regressions are carried out using a window of 200 observations and in each estimation we apply Hsiao (1981)'s sequential procedure outlined in Section 2 to determine the optimum $FPE_{\Delta S}(m, 0)$, $FPE_{\Delta S}(m, n)$, $FPE_{\Delta DIF}(m, 0)$ and $FPE_{\Delta DIF}(m, n)$ statistics.

A graphical presentation of the evolution of the difference between $FPE_{\Delta S}(m, 0)$ and $FPE_{\Delta S}(m, n)$ statistics is shown in Figure 1. This figure provides us with a view of the time-varying influence of DIF over S. As can be seen, most of the time the difference is positive, suggesting statistically significant Granger causality running from long-term interest rate differential towards the exchange rate. Nevertheless, there are some episodes where a negative difference is found, indicating that both variables are independent processes: September 2001-April 2001, January 2005 –September 2005 and March 2009- January 2011.

Regarding the results from the rolling regressions used to test Granger causality running from the US dollar-Euro exchange rate towards the USA-EMU long-term interest rate differential, Figure 2 indicates that difference between $FPE_{\Delta DIF}(m, 0)$ and $FPE_{\Delta DIF}(m, n)$ statistics is negative most of the time. This pattern suggests that DIF can be predicted more accurately by using the only its own past than by using past values of DIF and S (i. e., S does not Granger cause DIF). Interestingly, there are several episodes where we do find evidence of causality: October 1999-January 2000, December 2003-December 2005, and May 2007-October 2010.

5. Concluding remarks

This paper represents an attempt to examine the causal relationship between exchange rates and long-term interest rates. The period investigated extends from January 1999 to January 2011.

Despite the absence of any long-run trend common between both variables, Granger-causality tests revealed a short-run relationship among them does exist: the nominal US dollar-Euro exchange rate appears Granger caused by the long-term interest rate differential between USA and EMU Granger.

References:

Akaike, H. (1969): “Fitting autoregressive models for regression”, *Annals of the Institute of Statistical Mathematics*, Vol. 21, pp. 243-247

Alexius, A. (2001): "Uncovered interest parity revisited", *Review of International Economics*, Vol. 9, pp. 505–517

Carrión-i-Silvestre, J. L., Sansó-i-Roselló, A., Ortuño, M. A. (2001): “Unit root and stationarity tests’ wedding”, *Economics Letters*, Vol. 70, pp. 1–8.

Chinn, M. and Meredith, G. (2004): "Monetary policy and long-horizon uncovered interest parity", *IMF Staff Papers*, Vol. 51, pp. 409–430

Engel, C. (1996): "The forward discount anomaly and the risk premium: A survey of recent evidence", Journal of Empirical Finance, Vol. 3, pp. 123–192.

Flood, R. P. and Taylor, M. P. (1996): "Exchange rate economics: what’s wrong with the conventional macro approach?", in: Frankel, J., Galli, G. and Giovanni A. (eds.): *The Microstructure of Foreign Exchange Markets*, Chicago, pp. 262–301

Granger, C. W. J. (1969) “Investigating Causal Relations by Econometric Models and Cross-spectral Methods”, *Econometrica*. Vol. 37, pp. 24-36.

Hsiao, C. (1981). “Autoregressive modelling and money-income causality detection”, *Journal of Monetary Economics,* Vol. 7, pp. 85–106.

Johansen, S. (1991): “Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models”, *Econometrica*.Vol. 59, pp. 1551–1580.

Johansen, S. (1995). *Likelihood-based inference on cointegrated vectors autoregressive models*. Oxford: Oxford University Press.

Kwiatkowski, D. Phillips, P. C. B., Schmidt, P. and Shin, Y. (1992): “Testing the null hypothesis of stationarity against the Alternative of a unit root”, *Journal of Econometrics*, Vol. 54, pp.159–178

Thornton, D. L., and Batten, D. S. (1985). “Lag-length selection and tests of Granger causality between money and income”, *Journal of Money, Credit, and Banking*, Vol. 27, pp. 164-178.

Williams, E.J. (1959): *Regression analysis*. New York, Wiley.

Table 1. Augmented Dickey- Fuller tests for unit roots

Panel A: I (2) versus I (1)			
	τ_τ	τ_μ	τ
ΔS	-54.6516*	-54.6340*	-54.6602*
ΔDIF	-51.3264*	-51.3328*	-53.3218*
Panel B: I (1) versus I (0)			
	τ_τ	τ_μ	τ
S	-2.7689	-0.9900	0.2326
DIF	-2.7393	-0.8835	0.0356

Notes:
The ADF statistic is a test for the null hypothesis of a unit root.
τ_τ, τ_μ and τ denote de ADF statistics with drift and trend, with drift, and without drift, respectively.
* detones significance at the 1% level

Table 2. KPSS tests for stationarity

Panel A: I (1) versus I (2)		
	τ_τ	τ_μ
ΔS	0.1046	0.1455
ΔDIF	0.0451	0.0534
Panel B: I (0) versus I (1)		
	τ_τ	τ_μ
S	0.4691*	5.4484*
DIF	0.3856*	6.0761*

Notes:
The KPSS statistic is a test for the null hypothesis of stationarity.
τ_τ and τ_μ denote de ADF statistics with drift and trend, with drift, respectively.
* detones significance at the 1% level

Table 3. Cointegration tests

	Case 1	Case 2	Case 3	Case 4	Case 5
None	3.1033 (0.8346)	9.3433 (0.7038)	8.0286 (0.4624)	22.4854 (0.1247)	15.0112 (0.1208)
At most one	0.5572 (0.5175)	1.7805 (0.8309)	0.4687 (0.4936)	7.4981 (0.2954)	3.1411 (0.1396)

Notes:

We consider the five deterministic trend cases considered by Johansen (1995, p. 80–84):

- Case 1. The level data have no deterministic trends and the cointegrating equations do not have intercepts
- Case 2. The level data have no deterministic trends and the cointegrating equations have intercepts
- Case 3. The level data have linear trends but the cointegrating equations have only intercepts
- Case 4. The level data and the cointegrating equations have linear trends
- Case 5. The level data have quadratic trends and the cointegrating equations have linear trends

Parentheses are used to indicate p-values

Table 4. FPE statistics

Panel A: DIF Granger causes S					
$FPE_{\Delta S}(m,0)$	m	$FPE_{\Delta S}(m,n)$	n	F-statistic	comment
0.4861	0	0.4754	3	23.5785*	Causality: DIF → S
Panel B: S Granger causes DIF					
$FPE_{\Delta DIF}(m,0)$	m	$FPE_{\Delta DIF}(m,n)$	n	F-statistic	comment
3.1793	2	3.1808	1	0.60318	No causality: S → DIF

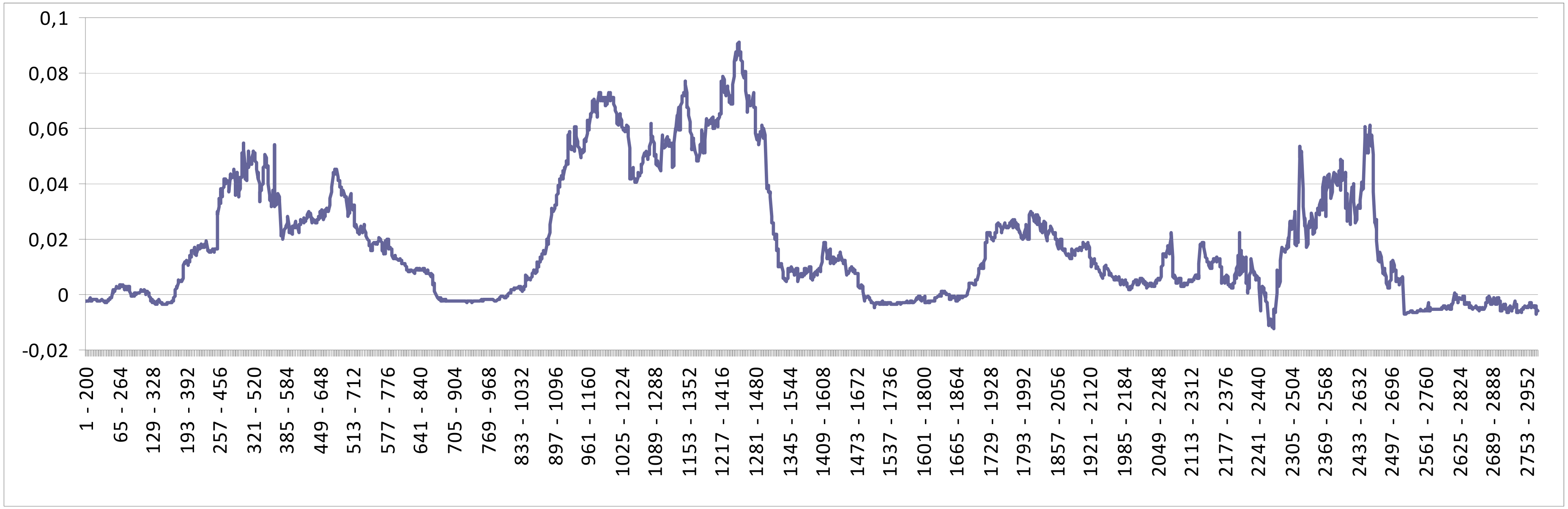
Note: * detones significance at the 1% level

Table 5. Willian-Kloot tests

Panel A: DIF → S		
	t-ratio	p-value
	-0.5000*	0.0000
Panel B: S → DIF		
	t-ratio	p-value
	-0.6719	0.5980

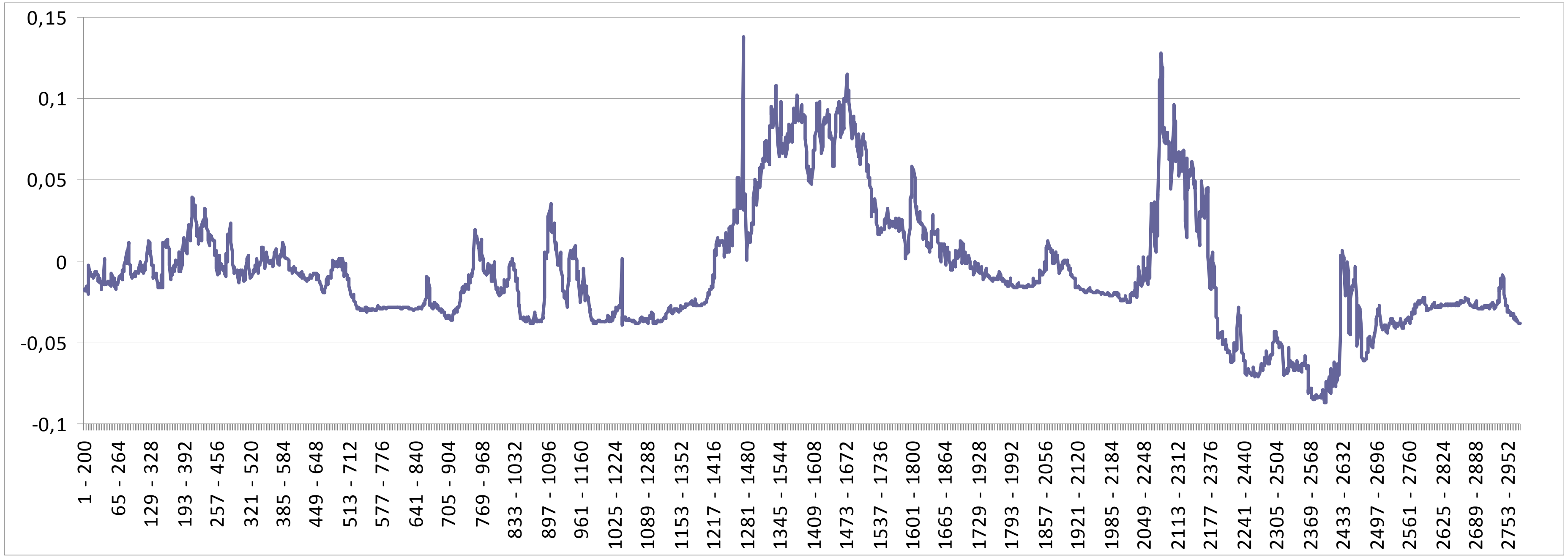
Note: * detones significance at the 1% level

Figure 1. Rolling regression results: DIF→ S



Note: Difference between $FPE_{\Delta S}(m, 0)$ and $FPE_{\Delta S}(m, n)$ statistics for each rolling regression using a window of 200 observations.

Figure 2. Rolling regression results: S→ DIF



Note: Difference between $FPE_{\Delta DIF}(m, 0)$ and $FPE_{\Delta DIF}(m, n)$ statistics for each rolling regression using a window of 200 observations.