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

Simón Sosvilla-Rivero
María del Carmen Ramos-Herrera

Corresponding author: Simón Sosvilla-Rivero  
Departamento de Economía Cuantitativa, Facultad de Ciencias Económicas y Empresariales, Universidad Complutense de Madrid, Campus de Somosaguas, 28223 Madrid, Spain, sosvilla@ccce.ucm.es

María del Carmen Ramos-Herrera  
Departamento de Economía Cuantitativa, Facultad de Ciencias Económicas y Empresariales, Universidad Complutense de Madrid, Campus de Somosaguas, 28223 Madrid, Spain,

March 2011

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 the 1999-2011 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, F31, F33, G15
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,

\[ X_t = \alpha_0 + \sum_{i=1}^{m} \delta_i X_{t-i} + \epsilon_t \]  

(1)

\[ X_t = \alpha_0 + \sum_{i=1}^{m} \delta_i X_{t-i} + \sum_{j=1}^{n} \gamma_j Y_{t-j} + \epsilon_t \]  

(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.

---

\(^1\) FPE\(_X\)(m,0) is computed using the formula: \( FPE\(_X\)(m,0) = \frac{T + m + 1 \text{SSR}}{T - m - 1} \), 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 \text{SSR}}{T - m - n - 1} \), 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 $\Delta X_t$ to $\Delta Y_t$ and from $\Delta Y_t$ to $\Delta X_t$, using the following error correction models:

\[
\Delta X_t = \alpha_0 + \beta Z_{t-1} + \sum_{i=1}^{m} \delta_i \Delta X_{t-i} + \epsilon_t \tag{3}
\]

\[
\Delta Y_t = \alpha_0 + \beta Z_{t-1} + \sum_{i=1}^{m} \delta_i \Delta X_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta Y_{t-j} + \epsilon_t \tag{4}
\]

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 $\beta$ 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 $\Delta X_t$ and $Y_t$ with $\Delta Y_t$ 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 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 $\hat{y}_1 = \hat{y}_2 = \ldots = \hat{y}_n = 0$.

[Insert Table 4 here]

As can be seen, the optimum order lag $m$ of $\Delta S_{t-j}$ ($\Delta DIFF_{t-j}$) when $\Delta S_t$ ($\Delta DIFF_t$) is regressed on its own past values and a constant only is one (two), while the optimum order lag $n$ of $\Delta DIFF_{t-j}$ ($\Delta S_{t-j}$) when $\Delta S_t$ ($\Delta DIFF_t$) is regressed on its own past values (whose order of lags is fixed at $m$), the past values of $\Delta DIFF_{t-j}$ ($\Delta S_{t-j}$) and a constant is three (one). On the other hand, $FPE_{\Delta S}(m, 0) > FPE_{\Delta S}(m, n)$ and $FPE_{\Delta DIFF}(m, 0) < FPE_{\Delta DIFF}(m, n)$, suggesting that Granger causality runs one-way from DIFF 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 $\Delta S_t$ are zeros, but we cannot reject the null hypothesis that all coefficients of the lagged $\Delta DIFF_t$ 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 $f_2$ 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 $f_1 - f_2$. A significantly negative value implies that $f_2$ is statistically superior to that of $f_1$ (and vice versa). Therefore, we generated forecasts for $\Delta S$ and $\Delta DIFF$ 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 $\Delta S_t$ can be better predicted by adding the information content of the $\Delta DIFF_t$, rather than by past values of $\Delta S_{t-j}$ alone. On the other hand, forecasting accuracy for $\Delta DIFF_t$ cannot be gained by considering also the information content of $\Delta S_{t-j}$. Therefore, these results reinforce our earlier conclusion about from Table 4.
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. In particular, we carried out 2776 regressions using a window of 200 observations. 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. Figures 2 and 3 show the distributions of the optimum order lags \(m\) and \(n\) when testing causality of DIF over S and S over DIF, respectively. As can be seen, in the two cases lag 1 is the most frequent both in \(m\) and \(n\), being consistent with the existence of serial correlation in the series.

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 3. 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. The first episode is associated with the increased risk aversion that followed the tragic events of 11 September and led to an appreciation of the euro against the dollar, intensified as a result of existing market concerns about the proper enforcement of accounting standards by companies in that country, the widening of negative interest rate in the euro area, market concerns about the imbalance in the current account of the emergence of a budget deficit and uncertainty about future economic growth prospects. As for the second episode (January 2005 –September 2005), it could be related to the market perceptions of an improvement in U.S. economic activity and a slower growth in the euro area, together with the rejection of the Treaty establishing a Constitution for Europe in referendums in France and the Netherlands in 2005. Finally, the last episode starting in March 2009 coincides with an appreciation of the euro in a climate of improving the situation of financial markets, a trend that was interrupted from December 2009 following the fiscal crisis in Greece, which led to episodes of instability, particularly severe in the second half of April and early May 2010, resulting in the euro exchange rate to depreciate against the dollar.

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 4 indicates that difference between $\Delta FPE_{DIF}(m, 0)$ and $\Delta FPE_{DIF}(m, n)$ 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. The first episode coincides with increasing concerns in financial markets that the US economy was growing at a rate that might lead to inflationary pressures in the economy, while in EMU, after the European Central Bank’s decision to raise interest rates on 4 November, market participants revised their long-term inflation expectations downwards and lowered the magnitude of the inflation risk premium required for holding euro-denominated bonds. As for the second episode (December 2003-December 2005), it can be associated with the changing perceptions of market participants with regard to inflationary pressures after of the sharp rise in oil prices and the outlook for the euro area economy, perceptions which were in turn closely related to changes in global macroeconomic prospects throughout this period. This led to some decoupling of long-term bond yield movements reflecting diverging views among market participants about the macroeconomic prospects and short-term interest rate expectations in the two economies. Finally, the last episode (May 2007-October 2010), the financial turmoil and the repricing of risk registered in the second half of 2007 created favourable investment opportunities outside EMU, being stimulated by the strengthening of the euro exchange rate.

[Insert Figure 4 here]

5. Concluding remarks

This paper represents an attempt to examine the causal relationship between exchange rates and long-term interest rates, contributing to the burgeoning literature on the empirical determinants of exchange rate movements. To that end, we analyse data for the US Dollar-Euro exchange rate and US-EMU bond yield differentials covering the period 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.

Acknowledgements

The authors gratefully acknowledged financial support from the Spanish Ministry of Science and Innovation (ECO2008-05565). María del Carmen Ramos-Herrera also acknowledges her grant (F.P.U.) from the Spanish Ministry of Science and Innovation (Ref. AP2008-004015).
References:


Table 1. Augmented Dickey-Fuller tests for unit roots

<table>
<thead>
<tr>
<th>Panel A: I (2) versus I (1)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>∆S</td>
<td>$\tau_\tau$</td>
<td>$\tau_\mu$</td>
<td>$\tau$</td>
</tr>
<tr>
<td>-54.6516*</td>
<td>-54.6340*</td>
<td>-54.6602*</td>
<td></td>
</tr>
<tr>
<td>∆DIF</td>
<td>-51.3264*</td>
<td>-51.3328*</td>
<td>-53.3218*</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: I (1) versus I (0)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>$\tau_\tau$</td>
<td>$\tau_\mu$</td>
</tr>
<tr>
<td>-2.7689</td>
<td>-0.9900</td>
<td>0.2326</td>
</tr>
<tr>
<td>DIF</td>
<td>-2.7393</td>
<td>-0.8835</td>
</tr>
</tbody>
</table>

Notes:
The ADF statistic is a test for the null hypothesis of a unit root. $\tau_\tau$, $\tau_\mu$ and $\tau$ denote the ADF statistics with drift and trend, with drift, and without drift, respectively. * denotes significance at the 1% level.

Table 2. KPSS tests for stationarity

<table>
<thead>
<tr>
<th>Panel A: I (1) versus I (2)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>∆S</td>
<td>$\tau_\tau$</td>
<td>$\tau_\mu$</td>
</tr>
<tr>
<td>0.1046</td>
<td>0.1455</td>
<td></td>
</tr>
<tr>
<td>∆DIF</td>
<td>0.0451</td>
<td>0.0534</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: I (0) versus I (1)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>$\tau_\tau$</td>
<td>$\tau_\mu$</td>
</tr>
<tr>
<td>0.4691*</td>
<td>5.4484*</td>
<td></td>
</tr>
<tr>
<td>DIF</td>
<td>0.3856*</td>
<td>6.0761*</td>
</tr>
</tbody>
</table>

Notes:
The KPSS statistic is a test for the null hypothesis of stationarity. $\tau_\tau$ and $\tau_\mu$ denote the ADF statistics with drift and trend, and with drift, respectively. * denotes significance at the 1% level.
### Table 3. Cointegration tests

<table>
<thead>
<tr>
<th></th>
<th>Case 1</th>
<th>Case 2</th>
<th>Case 3</th>
<th>Case 4</th>
<th>Case 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>3.1033</td>
<td>9.3433</td>
<td>8.0286</td>
<td>22.4854</td>
<td>15.0112</td>
</tr>
<tr>
<td></td>
<td>(0.8346)</td>
<td>(0.7038)</td>
<td>(0.4624)</td>
<td>(0.1247)</td>
<td>(0.1208)</td>
</tr>
<tr>
<td>At most one</td>
<td>0.5572</td>
<td>1.7805</td>
<td>0.4687</td>
<td>7.4981</td>
<td>3.1411</td>
</tr>
<tr>
<td></td>
<td>(0.5175)</td>
<td>(0.8309)</td>
<td>(0.4936)</td>
<td>(0.2954)</td>
<td>(0.1396)</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Panel A: DIF Granger causes S</th>
<th>FPE&lt;sub&gt;AS(m,0)&lt;/sub&gt;</th>
<th>m</th>
<th>FPE&lt;sub&gt;AS(m,n)&lt;/sub&gt;</th>
<th>n</th>
<th>F-statistic</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.4861</td>
<td>1</td>
<td>0.4754</td>
<td>3</td>
<td>23.5785*</td>
<td>Causality: DIF → S</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: S Granger causes DIF</th>
<th>FPE&lt;sub&gt;ADIF(m,0)&lt;/sub&gt;</th>
<th>m</th>
<th>FPE&lt;sub&gt;ADIF(m,n)&lt;/sub&gt;</th>
<th>n</th>
<th>F-statistic</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.1793</td>
<td>2</td>
<td>3.1808</td>
<td>1</td>
<td>0.60318</td>
<td>No causality: S → DIF</td>
</tr>
</tbody>
</table>

Note: * detones significance at the 1% level

### Table 5. Willian-Kloot tests

<table>
<thead>
<tr>
<th>Panel A: DIF → S</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.5000*</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: S → DIF</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.6719</td>
<td>0.5980</td>
</tr>
</tbody>
</table>

Note: * detones significance at the 1% level
Figure 1. Distribution of optimal lags $m$ and $n$ when testing causality from DIF to S

<table>
<thead>
<tr>
<th>Distribution of $m$</th>
<th>Distribution of $n$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Graph" /></td>
<td><img src="image2.png" alt="Graph" /></td>
</tr>
</tbody>
</table>

Figure 2. Distribution of optimal lags $m$ and $n$ when testing causality from S to DIF

<table>
<thead>
<tr>
<th>Distribution of $m$</th>
<th>Distribution of $n$</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3.png" alt="Graph" /></td>
<td><img src="image4.png" alt="Graph" /></td>
</tr>
</tbody>
</table>
Figure 3. Rolling regression results when testing causality from DIF to S

Note: Difference between $\text{FPE}_{\Delta S}(m, 0)$ and $\text{FPE}_{\Delta S}(m, n)$ statistics for each rolling regression using a window of 200 observations.
Figure 3. Rolling regression results when testing causality from S to DIF

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