# Over-Accepted Causality Hypothesis: Misspecification of Models, Missing Filters or Mimic Processes?

*Sadek Melhem*[*]
*Michel Terraza*[**]

**Abstract**

*In order to verify the strictly non linear nature of causal relationship, a procedure suggested by Bekiros and Diks (2008) was utilized, resorting to consecutive filtering of residuals via various processes. After application of a GARCH-BEEK filter, remaining significant unidirectional nonlinear causal relationship was found running from exchange rate to oil prices. Thus, we investigate whether rejection of null hypothesis is due to misspecification of used GARCH model or other reasons. Hence, a Mackey Glass filter was used to eliminate the bias caused by deterministic chaos which resulted in the acceptance of null hypothesis according to which oil prices do not cause variations in exchange rate and vice versa. It can be concluded that, firstly, its plausible that Mackey Glass function, in filtering processes, takes slightly into account fluctuations that can be classified as conditional heteroskedasticity. Secondly, chaotic structure amplified by a white noise process might mimic a conditionally Heteroskedastic one, which can explain the reaction of the nonlinear causality test after GARCH filtering.*

---

[*] LAMETA, Department of Economics, University of Montpellier I, France. sadek.melhem@lameta.univ-montp1.fr
[**] LAMETA, Department of Economics, University of Montpellie I, France. mterraza@lameta.univ-montpI.fr

**Keywords:** Non parametric nonlinear Granger causality, GARCH-BEKK, Mackey Glass function, oil prices and exchange rates.

## 1. Introduction

Since the introduction of an operational definition of causality between two variables by Granger (1969), the notion has been a starting point for testing a null hypothesis of one variable not causing the other to vary. But testing has most often been carried out in a linear framework. These tests have proved to be of high power in uncovering linear causal relationships while this power disappears in the case of nonlinear causal relationships. Consequently, there has been growing interests in generalizing the test into nonlinear framework. First, non parametric non causality tests were introduced by Beak and Brock (1992), Hiemstra and Jones (1994), Bell, Kay and Mally (1996), Su and White (2003) for which the enigma consisted in the power of test. Moreover, Péguin-Feissolle and Terasvirta (1999) proposed a general nonlinear causality test based on Artificial Neural Networks (ANN), with the unique property of increased test power for small samples. On the other hand, Diks and Panchenko (D&P) (2006) extended the Hiemstra-Jones test in order to accommodate it to the presence of conditional heteroskedasticity, thus granting it more test power. Finally, Hristu-Varsakelis and Kyrtsou (2008) proposed a parametric test that treats the non linear causality in the presence of a certain class of chaos process.

In order to examine the possible existence of nonlinear causal relationship between oil prices and exchange rates[2], we use D&P nonparametric nonlinear causality test plus a filtering procedure to examine whether existing causal relationships are nonlinear in nature.

[2] According to studies by Amano and Van Norden (1998) and Mignon and al. (2005), causality runs linearly from oil price variation to exchange rate changes. In another hand, Melhem and Terraza (2007) found that exchange rates linearly caused oil prices. This change in direction was studied by Blanchard and Gali (2008), who showed that causal link nature changes over time.

Then an attempt to extend filtering procedure was made by adding a chaotic structure filter in order to comprehend the real reason behind the rejection of null hypothesis of the test applied on GARCH-BEEK filtered residuals. D&P considered that rejection of the null hypothesis was due to misspecification of the GARCH filtering model, since the correct model is not known in the context of real economic data. Therefore, the aim of this paper is to highlight underlying reasons for null hypothesis rejection, particularly after GARCH filtering.

Thus, the paper is structured as follows: After giving a brief introduction in the first section, we describe the nonparametric nonlinear causality test D&P in section 2. Then we present data used and the summary statistics in section 3. Empirical results are reported in section 4. The final section draws the conclusions.

## 2. Nonparametric Test for Nonlinear Granger Causality

After illustrating the problem concerning the serious size distortion in the Hiemstra and Jones (1994) nonlinear causality tests, by showing that the test statistic does not converge to zero in probability under the null hypothesis as the sample size increases, D&P introduced a new non-parametric test for Granger non causality which avoids over-rejection of null hypothesis observed in the frequently used test of Hiemstra and Jones. They showed that the reason for over-rejection in the Hiemstra-Jones (H&J) test is that the test statistic ignores possible variations in the conditional distribution that may occur under null hypothesis. Based on analytical results, the global test was replaced by one having an $\varepsilon$ that tends to zero at the appropriate rate, which automatically takes into account the variations in concentrations.

Accordingly, D&P used a nonlinear granger causality test based on nonparametric estimators of temporal relations. Let ($X_t, Y_t, t \geq 1$) two scalar-valued strictly stationary time series. Testing if $X_t$ Granger causes $Y_t$, supposes that:

$$(Y_{t+1},...,Y_{t+k})|(F_{X,t},F_{Y,t}) \sim (Y_{t+1},...,Y_{t+k})|F_{X,t}$$

Where $k \geq 1$, in practice $k = 1$ And $(F_{X,t},F_{Y,t})$ is a vector of historical values containing the past observations of $X_t, Y_t$[3]. And let ~ denote equivalence in distribution. D&P considered delay vectors denoted by $X_t^{l_x} = (X_{t-l_x+1},...,X_t)$ and $Y_t^{l_y} = (Y_{t-l_x+1},...,Y_t)$, where $l_x, l_y \geq 1$. Under null hypothesis, the non-significance of past observations of $X_t^{l_x}$ in the determination of $Y_{t+1}$ is tested, i.e.:

$$H_0 : Y_{t+1}|(X_t^{l_x};Y_t^{l_y}) \sim \mathrm{Y}_{t+1}|Y_t^{l_y}$$

Under the null hypothesis the computed *t-statistic* consists of weighted averages of local contributions $\hat{f}_{x,y,z}(X_i, Y_i, Z_i)\hat{f}_y(Y_i) - \hat{f}_{x,y}(X_i, Y_i)\hat{f}_{y,z}(Y_i, Z_i)$ that tend to zero in probability and is expressed as follows:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)}\sum_i \hat{f}_{x,y,z}(X_i,Y_i,Z_i)\hat{f}_y(Y_i) - \hat{f}_{x,y}(X_i,Y_i)\hat{f}_{y,z}(Y_i,Z_i)$$

Where $l_x = l_y = 1$, if $\varepsilon_n = Cn^{-\beta}$, the bandwidth depends on the sample size, and the constant C is positive and $\beta \in \left(\frac{1}{4},\frac{1}{3}\right)$. Under strong mixing, the test statistic $T_n$ satisfies:

[3] Granger causality can also be detected by comparing the residuals of a fitted Autoregressive model on $Y_t$ with those obtained by regressing $Y_t$ on infinite past value of both $X_t$ and $Y_t$

$$\sqrt{n}\,\frac{\left(T_n\left(\varepsilon_n\right)-q\right)}{S_n}\xrightarrow{d} N\left(0,1\right)$$

Where $\xrightarrow{d}$ denotes convergence of the distribution and $S_n$ is an estimator of the asymptotic variance of $T_n$.

The D&P test offers a solution to the distortions of the actual size of H&J test in the presence of dependence in conditional variance. An alternate solution is to filter out the conditional heteroskedasticity by using an ARCH specified filter that can remove the bias in results. According to D&P, a filtering procedure has several drawbacks, first, it may affect the test power, second, it seems impossible in practice to establish a model that traces out the exact underlying structures of a variable, and hence the ARCH filter used to remove the conditional heteroskedasticity is likely to be misspecified. As a result, the misspecified ARCH filter might not be able to remove a large proportion of the source of bias, which can affect the sensitivity of the H&J test.

**3. Data and Summary Statistics**

Before undertaking a statistical analysis that examines the predominant relationship between Effective Exchange Rates of Dollar (EERD) and Oil prices (OIL), we shall describe the data used for the analysis. The available data consists of daily closing (5 days) real effective exchange rate of the dollar defined in terms of the price adjusted major currency index and the real oil price denominated in the US dollar. The oil price series is the US dollar spot price of West Texas Intermediate Crude Oil deflated by the US consumer price index over January 1999 – December 2008. So, the data are log-differenced to give DLEERD and DLOIL and are taken from Federal Reserve and Energy Information Administration respectively. Table 1 provides summary statistics of data.

The Augmented Dickey Fuller unit root test shows that both series are stationary in first difference. The Engel (1982) test result confirms the presence of heteroskedasticity. Moreover, both series exhibit a high correlation. Excess Kurtosis relative to the standard distribution is revealed. The distribution of the series is positively skewed for OIL prices and negatively for EERD. The combination of significant asymmetry and leptokurtosis indicates that the oil prices and exchange rate series are not normally distributed which concords with Jarque-Bera statistics. In testing the presence of chaotic structure, we use the non-parametric neural network Lyapunov exponent's test of Shintani and Linton (2004). The estimated results for each series are presented in table 1 along with the p-value for the null hypothesis of positive Lyapunov exponent $(H_0 : \lambda \geq 0)$. The block length and the number of blocks used for sub sampling estimates are 50 and 55, respectively. For all cases, the Lyapunov exponents from full sample estimation are positive, so, the positivity hypothesis is significantly accepted at the 1% level. Similar strong evidence is obtained from sub sample estimations (ES). Therefore, both series exhibit a chaotic process in structures.

## 4. Empirical Results

In order to investigate the results presented in Table 2, we allow for the following observations: focusing on rejection of the null hypothesis of non causality at 1% significance level (column 1), the test shows strong evidence of unidirectional nonlinear influence of dollar exchange rate on oil prices over the sample period. This relationship expressed as a *sequential arrival of information* model was introduced by Jennings et al. (1981). The model assumes that such innovation reaches only one

Table 1: Statistics Summary

| | URT | Q(12) | ARCH-LM | $\lambda$ *Full* | *Block* | *ES* | Skew | Kurt | JB |
|---|---|---|---|---|---|---|---|---|---|
| DLOIL | -52.0 | 30.4 | 0.30 | 2.70 | 2.60 | 2.70 | 0.18 | 6.26 | 3040 |
| | (0.00)* | (0.00)* | (0.00)* | (0.00)* | (0.00)* | (0.00)* | | | (0.00)* |
| DLEERD | -48.5 | 55.58 | 0.039 | 0.56 | 0.23 | 0.55 | -0.07 | 1.96 | 107 |
| | (0.00)* | (0.00)* | (0.05)* | (0.00)* | (0.00)* | (0.00)* | | | (0.00)* |

* Reject the null hypothesis at 5% significant level. For each lag of Lyapunov exponents, the numbers of hidden units are selected based on BIC.

participant at a time, leading to final information equilibrium only after a sequence of transitional equilibriums has occurred. Thus according to this model, lagged absolute values of exchange rates may have the ability to predict oil prices.

The results presented in table 2 (first column) suggest that there exists some significant and persistent non-linear causal influence of exchange rate on oil prices. However, even though nonlinear causality was detected, it seemed proper to proceed as Bekerios and Diks (2008) by reapplying the test on VAR filtered residuals to examine whether the detected causality is strictlynonlinear in nature, with VAR parameterization based on the Schwartz Information Criterion (SIC).

Table 2: D&P Test and Statistics Tests on GARCH BEEK Residuals

| | Before Filtering | After VAR filtering | After GARCH-BEEK filtering |
|---|---|---|---|
| Dloil → Dleerd | 0.918<br>(0.17) | -1.03<br>(0.15) | 0.92<br>(0.17) |
| Dleerd → Dloil | 3.075<br>(0.00)* | -1.89<br>(0.03)** | 1.31<br>(0.06)*** |

| | ARCH-LM | $\lambda$ *Full* | $\lambda$ *Block* | $\lambda$ *ES* | Q(12) | J.B |
|---|---|---|---|---|---|---|
| Dloil | 0.096<br>(0.12) | 2.41<br>(0.00)* | 2.15<br>(0.00)* | 2.41<br>(0.00)* | 16.03<br>(0.07)*** | 305.7<br>(0.00)* |
| Dleerd | 0.081<br>(0.162) | 0.26<br>(0.03)** | 0.31<br>(0.02)** | 0.25<br>(0.03)** | 6.71<br>(0.09)*** | 45.36<br>(0.00)* |

* Rejection of null hypothesis at 1% significant level.
** Rejection of null hypothesis at 5% significant level.
*** Rejection of null hypothesis at 10% significant level.
Results are shown for bandwidth value of 1 and $l_x = l_y = 1$.

Statistics shows that both series are empty of heteroskedasticity, but there exists of chaotic and slightly auto-correlated in structures residuals. Furthermore, residuals are not normally distributed which concords with Jarque-Bera statistics.

In comparing results presented in column 1 to those of column 2, it can be noticed that test results have not changed globally, but statistical significance of obtained statistics has become less obvious after filtering. It's plausible that the disappearance of the linear structure is consequential enough to impact the statistical significance. It is also believed that volatility in series might induce nonlinear causality. Thus, in order to apprehend the entire variance-covariance structure of the EERD-OIL interrelations it is possible to take advantage of the volatility transmission mechanism after controlling for conditional heteroskedasticity using the GARCH-BEKK model of Engel and Kroner (1995).

To the aim cited above, causality analysis are reiterated on the GARCH-BEKK filtered series after using the estimated VAR residuals for conditionally standardized oil prices and exchange rates series. Results obtained from the nonparametric nonlinear causality test strongly indicate evidence of exchange rate affecting oil prices (column 3). Although these results seem similar to the previous (obtained after VAR filtering), the statistical significance of statistics have become less strong. The difference in statistical significance indicates that the nonlinear causality is partially due to simple volatility effects. In other words, results indicate that: first, volatility effects induce a short run causal relationship from exchange rate to oil prices, and second, volatility effects are probably not the only ones inducing nonlinear causality.

## 4.1 Causality Testing on Mackey Glass-GARCH-BEEK Filtering Residuals

As previously established by D&P, significance of test statistics has been found to be less pronounced after each filtering step. Moreover, after GARCH-BEEK filtering, it was noticed that there still remained some unknown structure in residuals, and according to D&P analysis, this is due to misspecification of GARCH filter. However, we interrogate the soundness of this interpretation and propose a means of verification by adding a new filtering step that can filter out deterministic chaos from residuals. Therefore, to eliminate any ambiguous situation where chaotic structure may be responsible for rejecting the null hypothesis, we propose to filter residuals by Mackey Glass model in order to remove deterministic dynamics from residuals. This solution permits us to verify whether the structure remaining in GARCH-BEEK filtered residuals is due to misspecified ARCH filter or to other reasons existing in the process.

It is known that distinguishing between noise levels are very difficult as much as it is between both chaotic and stochastics processes (Wolff, 1990). A possible explanation is that financial series may include both chaotic and heteroskedastic structures. Therefore, the chosen system to filter VAR filtered residuals is bivariate MG-BEKK models of Kyrtsou and Vorlow (2009). One of the main advantages of this model lies in its flexibility in testing non linearity in mean and in variance. Aiming to compare filtering performance of GARCH-BEKK models, Mackey Glass model and combined MG-BEKK model amongst themselves, computer simulations were executed in the presence of complex structures (chaotic stochastics), and results showed that combined models appear to be of more filtering power than simple ones. As a consequence, MG-BEKK filter has an important advantage in the presence of complex structure. The model is given by the following equation:

$$DLOIL_t = \alpha_1 \frac{DLOIL_{t-\tau_1}}{1+DLOIL_{t-\tau_1}^{c_1}} - \delta_1 DLOIL_{t-1} + \alpha_2 \frac{DLEERD_{t-\tau_2}}{1+DLEERD_{t-\tau_2}^{c_2}} - \delta_2 DLEERD_{t-1} + \varepsilon_t$$

$$DLEERD_t = \alpha_1 \frac{DLEERD_{t-\tau_1}}{1+DLEERD_{t-\tau_1}^{c_1}} - \delta_1 DLEERD_{t-1} + \alpha_2 \frac{DLOIL_{t-\tau_2}}{1+DLOIL_{t-\tau_2}^{c_2}} - \delta_2 DLOIL_{t-1} + \varepsilon_t$$

We must note that the choice of lags $\tau$ and $c$ is crucial since they determine the dimension of the system. The $\varepsilon_t$ vector is assumed to be normally distributed with the conditional variance-covariance positive[4] definite matrix $H_t$, i.e., $\varepsilon_t | \phi_{t-1} \sim N(0, H_t)$, $\phi_{t-1}$ is the set of information available at time t-1**.** The residuals are obtained by the whitening matrix transformation $H^{1/2}\varepsilon_t$.

$$\varepsilon_t = H_t^{1/2} v_t, \qquad H_t = C'C + \sum_{i=1}^{p} A_i' \varepsilon_{t-i} \varepsilon_{t-i}' A_i + \sum_{j=1}^{q} B_j' H_{t-j} B_j$$

With $$C = \begin{pmatrix} C_{11} & C_{12} \\ 0 & C_{22} \end{pmatrix}, \quad A_i = \begin{pmatrix} a_{11}^{(i)} & a_{12}^{(i)} \\ a_{21}^{(i)} & a_{22}^{(i)} \end{pmatrix}, \quad B_j = \begin{pmatrix} b_{11}^{(j)} & b_{12}^{(j)} \\ b_{21}^{(j)} & b_{22}^{(j)} \end{pmatrix}$$

Table 3: D&P Test on MG-BEEK Residuals

| | After MG filtering |
|---|---|
| $Dloil \rightarrow Dleerd$ | 0.179<br>(0.42) |
| $Dleerd \rightarrow Dloil$ | -0.53<br>(0.29) |

- Results are shown for bandwidth value of 1 and $l_x = l_y = 1$. $\tau_1 = \tau_2 = 1$ and $c_1 = c_2 = 2$ the delay and c specification where based on the Schwartz Information Criterion (SIC).

Reiteration of D&P test on MG-BEKK filtered residuals are reported in Table 3. The results show that nonlinear causal relationships detected previously in residuals have now disappeared. This gives rise to several questions i.e., how do these results explain this phenomenon? Why after simple GARCH-BEKK model the null hypothesis is rejected and after that MG-BEKK is accepted? How can Mackey Glass filter explain the remaining structure in GARCH-BEEK residuals, if this structure is conditional heteroskedasticity? How can D&P test reacts to the presence

[4] Gourieroux (1997) gives sufficient restrictions on $A_t$ and $B_t$ in order to guarantee that $H_t$ is always positive definite.

of certain class of chaos in residuals? To answer these questions, two explanations can be drawn from this result.

It's plausible that D&P's conclusion on the remaining structure in GARCH-BEEK residuals can be taken into account according to which, the problem is due to misspecified GARCH model. In this case, the focus then becomes on power of Mackey Glass model in the presence of conditional heteroskedasticity in residuals. As we know, time delay differential equation is a simple equation that can generate complex dynamics including chaos. Mackey Glass Equation are infinite dimensional systems. This is because it is necessary to specify an initial function over the time interval $[-\tau, 0]$ in order for the solution to be well defined and to be able to integrate the equation. Mackey-Glass equation recognized that increasing the value of $\tau$ increases the dimension of the attractor in chaotic systems and then the degrees of freedom (Farmer, 1982), and thus probably sharing a slight characteristic of stochastics processes but with different power (Tong, 1990).

Graph 1b presents the "*spectral density*" based on the Wavelet transform[5]. The wavelet transform is commonly used in the time domain. For example, wavelet noise filters are constructed by calculating the wavelet transform for a signal and then applying an algorithm that determines which wavelet coefficients should be modified. (Wavelet coefficients are the result of the high pass filter applied to the signal or to the combinations of low pass filters of the signal). Although these coefficients are associated with frequency components, they are modified in the time domain (each coefficient corresponds to a time range). However, it's possible to read from graph 1b that Mackey Glass model's computed spectral density shows occupation of all frequency bands. Moreover, surprisingly, the spectral density of Mackey Glass model is established in high frequency bands with slight amplitude, where ARCH

[5] A transform which localizes a function both in space and scaling and has some desirable properties compared to the Fourier transform. The transform is based on a wavelet matrix, which can be computed more quickly than the analogous Fourier matrix.

model exist strongly with high amplitude (graph 3b). Here, we interrogate the power of Mackey Glass function in apprehending fluctuations that can be classified as conditional heteroskedasticity.

In order to illustrate this enigma, we simulate 4000 points of mixed processes containing chaos and conditional heteroskedasticity. Then, we applied the ARCH test on series before and after both Mackey Glass and logistic function filters. In comparing the performance of tests, we observe that ARCH coefficient power is reduced after Mackey Glass filtering, while the ARCH coefficient remains stable after the logistic filter (table 4). Thus, this result can reinforce the argument that Mackey Glass function, in filtering process, takes slightly into account certain fluctuations that can be classified as conditional heteroskedasticity. This argument can explain the fact that after MG-BEKK filter, residuals are empty from any structure.

Table 4: ARCH LM Test on Mixture Structure

| | ARCH before filter | ARCH after filter |
|---|---|---|
| Logistic Function | 0.295<br>(0.00) | 0.294<br>(0.00) |
| Mackey Glass Model | 0.295<br>(0.00 | 0.265<br>(0.00) |

Another plausible explanation is the mimic in the process. It is known though that distinguishing chaotic process from stochastic ones can be a very difficult exercise (Wolf 1990). In addition, in presence of white noise processes it was determined that chaotic processes could exhibit behaviour close to that of stochastic ones. In the same vein, Chen (1988) proved that the autocorrelation function of logistic function resembled those of white noise processes just as Guégan (2003) demonstrated that Henon map trajectories also imitated white noise processes in behaviour. Moreover, it was also discovered that filtering might affect original data dimension attributing it to a stochastic-like structure (Chen 1993).

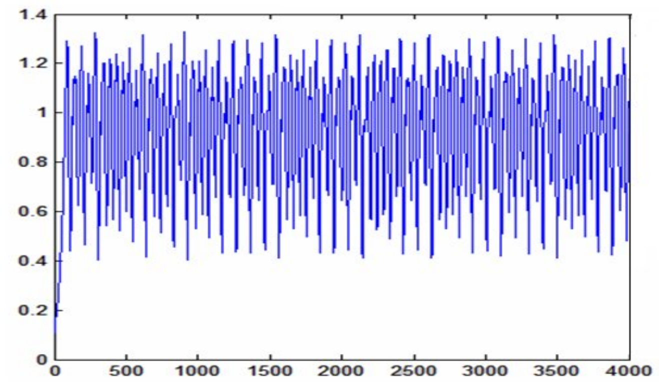
In order to understand the reason for D&P test's reactions in the presence of chaos, let us proceed as follows: firstly, 4000 points of a trajectory simulated by Mackey Glass equation (graph 1a). Then, this chaotic structure is amplified by combining it to a white noise process (graph 2a). Finally, we simulate a random walk trajectory following an ARCH (1) model, i.e. evolution of prices in presence of a conditional Heteroskedastic process (Graph 3a). In comparing Graphs 1a 2a and 3a we note that: as observed in Graph 1a, in the absence of noise, it is possible to clearly identify chaotic behaviours in times series. On the contrary, when these chaotic behaviours are amplified by combining them with white noise (Graph 2a), the resulting process exhibits behaviour over time, similar to that of an ARCH process. Meaning that, chaotic processes, in certain cases, may be able to mimic stochastic behaviours[6].

To support our analysis, we reapply ARCH test on amplified series to detect presence of heteroskedasticity in the structure. We note that ARCH model displays statistically significant parameters at 5% level (0.03, *p-value*), i.e. ARCH filter can lead to detection of spurious conditional heteroskedasticity. This fact can account for D&P test's reaction to chaos in GARCH-BEEK filtered residuals. Furthermore, acceptance of the null hypothesis according to which there exists no causal relationship between oil prices and exchange rates can reinforce this view.

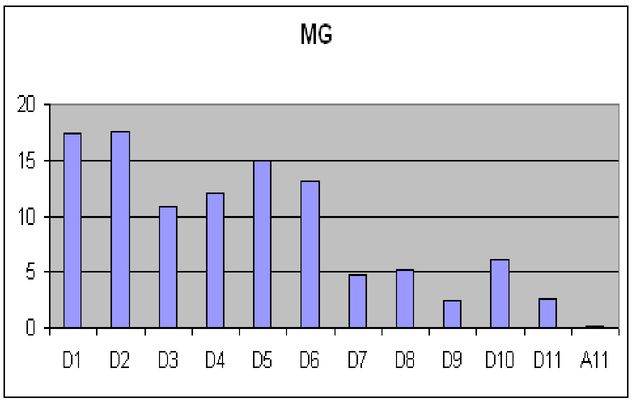
Overall, filtering has the effect of whitening data, and hence reducing tests' power. Thus, the aim of filtering processes is to obtain a white noise, where results can be arbitrary. We note from Table 5 that residuals' structure is on the one hand heteroskedasticity free

[6] Chen (1993), shows that chaos signals can explain about 70 percent of variance in de-trended cycles.

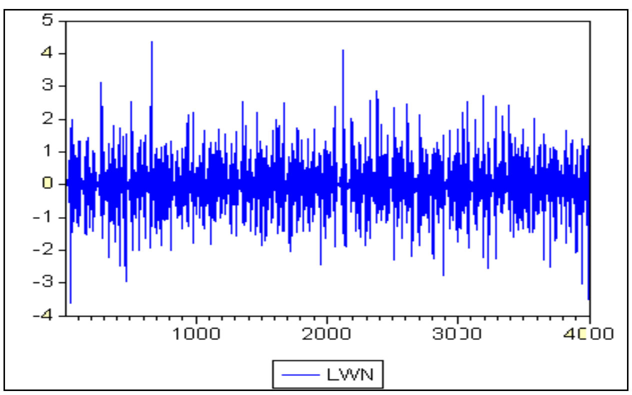
Graph 1a: Pseudo-random Trajectory of MG Model



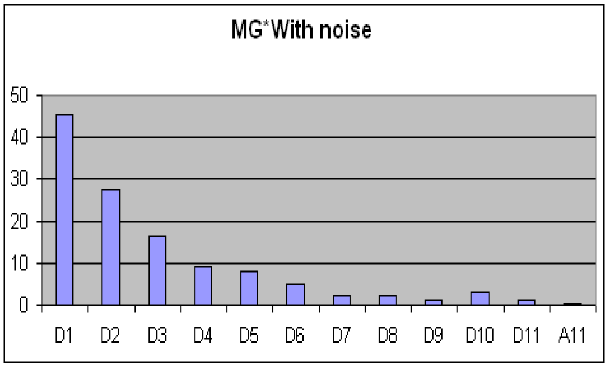

Graph 1b: Spectral Density of MG Model



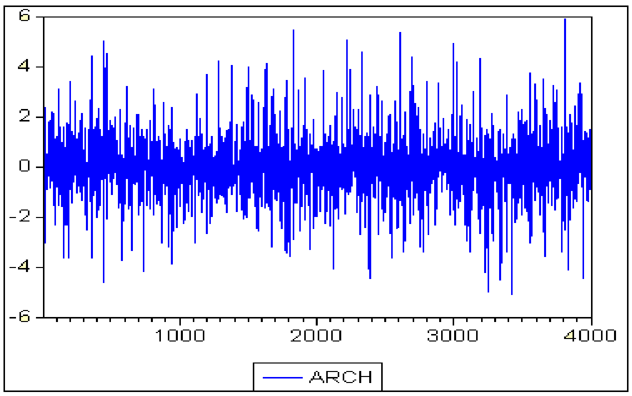

Graph 2a: MG Model Amplified by White Noise



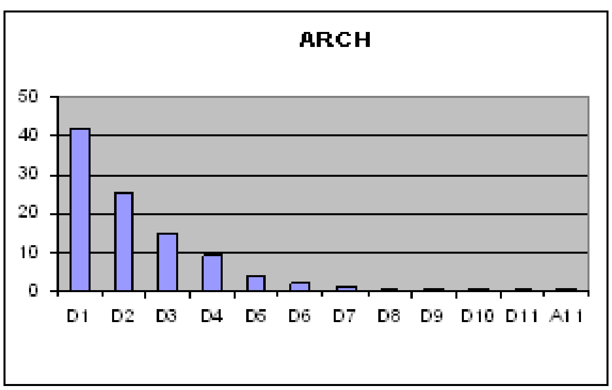
Graph 2b: Spectral Density of MG*White Noise




Graph 3a: ARCH (1) Structured Series (Random)




Graph 3b: Spectral Density of ARCH Model



and their chaotic nature comes with non auto-correlation. On the other hand, the combination of significant asymmetry and leptokurtosis indicate that the oil prices and exchange rate series slightly deviates from normal distribution.

Table 5: Descriptive tests on MG--BEKK filtered residuals

| | ARCH-LM | $\lambda$ | | Q(12) | J.B |
|---|---|---|---|---|---|
| | | *full* | *ES* | | |
| Dloil | 0.015<br>(0.44) | -2.8<br>(0.45) | -2.9<br>(0.43) | 7.88<br>(0.79) | 52.34<br>(0.00)* |
| Dlreed | 0.046<br>(0.82) | -4.67<br>(0.92) | -4.67<br>(0.98) | -0.001<br>(0.88) | 15.55<br>(0.05)** |

* Null hypothesis rejected at 1% significant level, ** at 10% significant level. ( ) is the p-value.

## 5. Conclusion

D&P results emerge from unidirectional nonlinear causal relationships running from exchange rate to oil prices. As suggested by Bekiros and Diks (2008), we filter our series to ensure whether the relationship between exchange rates and oil prices is non-linear in nature. Then, after adjusting for volatility effects, there is still evidence of unidirectional nonlinear relationships running from exchange rate to oil prices. D&P argued that the structure remained in residuals filtered either due to misspecification in GARCH model or to significance observed only on higher order moments. To verify the soundness of this reason, we proceed as follows:

To eliminate any ambiguous situation where chaotic structure may be responsible for the rejection of the null hypothesis, we use Mackey Glass model to get rid of the chaos structure from residuals. This solution permits us to verify whether the persistence of some structure in these filtered residuals is due to misspecified ARCH filter or to existence of other reasons. However, results show that after MG filtering, nonlinear causal relationship is nonexistent. In order to verify the robustness of our results reasoning, two explanations can be drawn:

First, Mackey Glass model, in filtering data process, takes slightly into account certain class of conditional heteroskedasticity. This argument can explain the fact that after Mackey Glass filter, residuals are empty from any structure. Second, series amplified by combining Mackey Glass and white noise exhibits behaviour over time that resembles that of an ARCH process, which leads to the conclusion that in some cases, chaotic processes may be disguised as stochastic ones. As a consequence, D&P test react to spurious conditionally heteroskedastic existing in residuals, and reject the null hypothesis.

## References

Baek, E. and Brock, (1992a). A General Test for Nonlinear Granger Causality: Bivariate Model, Working Paper. Iowa State University and University of Wisconsin, Madison.

Bekiros, S., and Diks, C. (2008). The Nonlinear Dynamic Relationship of Exchange Rates: Parametric and Nonparametric Causality Testing, Economics Energy, 30, pp. 2673-2685.

Bell, D., Kay, J. and Malley, J. (1996). A Nonparametric Approach to Nonlinear Causality Testing, Economics Letters, 51, 7-18.

Chen, P (1988), Empirical and Theoretical Evidence of Economic Chaos, System Dynamics Review, 4, Nr 1–2, PP. 81–108.

Chen, P., (1993). Searching for Economics Chaos: A Challenge to Econometric Practice and Non Linear Tests. In Day, R.H., Chen, P. (Eds), Nonlinear Dynamics and Evolutionary Economics. Oxford University Press, 217-252.

Diks, C. and Panchenko, V. (2006). A New Statistic and Practical Guidelines for Nonparametric Granger Causality Testing. Journal of Economic Dynamics & Control, 30, 1647-1669.

Engel, R.F, and Kroner, F. H. (1995). Multivariate Simultaneous Generalized ARCH, Econometric Theory, 21, 122-150.

Farmer, J.D. (1982). Chaotic Attractors of an Infinite-dimensional Dynamical System, *Physica* D, 4(3).

Gourieroux, C. (1997). ARCH Models and Financial Applications. Springer Verlag.

Granger, C. (1969). Investigating Causal relations by econometric model and across-spectral methods. Econometrica 37, 424-438.

Guégan, D. (2003). Le chaos en Finance : Approche Statistique, Economica.

Hiemstra, C. and Jones, J. (1994). Testing for Linear and Nonlinear Granger Causality in the Stock Price Volume Relation. The Journal of Finance, 49, 5, 1639-1664.

Hristu-Varsakelis, D. and Kyrtsou D., (2008). Evidence for Nonlinear Asymmetric Causality in US Inflation, Metal, and Stock Returns, Discrete Dynamics in Nature and Society, 138547.

Jennings, R., Starks, L, and Fellingham, J. (1981). An Equilibrium Model of Asset Trading with Sequential Information Arrival, Journal of Finance 36, 143-161.

Kyrtsou C., and Vorlow C. (2009). Modelling Non Linear Comovements between Time Series, Journal of Macroeconomics, 31, 200-211.

Lorenz, E. N. (1963). Deterministic Non Periodic Flow, *Journal of Atmosphere sciences*, 20, 130-141.

Mackey, M., and Glass L. (1977). Oscillation and Chaos in Physiological Control Systems, Science, 50, 287-289.

Mackey, M. C. (2007). Adventures in Poland: Having Fun and Doing Research with Andrzej Lasota, Mat. *Stosow*, 5-32.

Melhem S., and Terraza M. (2007). The Oil Price and the Dollar Reconsidered; Commodity Modelling and Pricing: Methods for Analyzing Resource Market Behavior, Chap 4, Wily & sons.

Peguin-Feissolle, A., and Terasvirta, T. (1999). A General Framework for Testing the Granger Non Causality Hypothesis. SSE/EFI Working Paper Series in Economics and Finance. No, 343.

Rössler, O.E. (1979). An Equation for Hyper Chaos, *Physics Letters. A*, Vol. 71, pp. 55-157.

Sintani, M., and Linton O. (2004). Non Parametric Neural Network Estimation of Lyapunov Exponents and a Direct Test for Chaos, Journal of Econometrics, 120, 1, 1-33.

Su, L., and White, H. (2003). Nonparametric Hollinger Metric Test for Conditional independence. Technical Report, Department of Economics, USCD.

Tong, H.W. (1990). Non Linear Time Series. A Dynamical System Approach, Charendon Press, Oxford.

Wolff, R.C.L. (1990). A Note on the Behaviour of the Correlation Integral in the Presence of a Time Series, Biometrica, 77, 4, 689-697.

Wolff, R.C.L. (1992). Local Lyapunov Exponents: Looking Closely at Chaos, Journal of the Royal Statistical Society, B, 54, 2, 353-371.