Analysing the Dynamics between U.S. Inflation and Dow Jones Index Using Non-Linear Methods

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Analysing the Dynamics between U.S. Inflation and Dow Jones Index Using Non-Linear Methods*

Stella Karagianni and Catherine Kyrtsou

Abstract

A growing body of literature concentrates on the linear dependence between stock returns and inflation. Although the recent empirical evidence suggested the presence of complexities, to our knowledge only a few works have investigated the existence of a potential nonlinear stock returns-inflation relationship. In order to study in more depth the dynamic attributes of this puzzle, we suggest a quite different framework where the primary goal is to explore the association between their underlying dynamics. Through the use of the Recurrence Quantification Analysis (Webber and Zbilut (1994)), the test for structural breaks of Bai and Perron (1998) and the test for nonlinear causality of Diks and Panchenko (2006), we find evidence in favour of negative nonlinear linkages between the inherent dynamics of inflation and stock returns. The presence of nonlinearity reinforces uncertainty. As long as inter-dependences are complex and nonlinear, small perturbations in fundamentals can lead to unexpected propagations within the financial system.

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1. Introduction

Fisher (1930) proposed that the expected nominal return on an asset should equal the expected real return plus expected inflation. He hypothesized that the expected real rate is determined by real factors such as the productivity of capital and time preference of savers, and is independent of the expected inflation rate. Following Fisher Hypothesis, economists thought that this relation could be easily extended to common stocks. Consistent with the view that stocks represent ownership of physical capital assets, their real value should be independent of the rate of inflation.

According to Canto et al. (1985) changes in the money supply can cause inflation. So, a positive association between changes in the money supply and stock returns would imply a positive association between inflation and stock returns. They explain that in order to maintain a monetary view of inflation, the monetary aggregate must be determined exogenously. In principle this is the case since the monetary base is under the control of government authorities and can be assumed to be exogenous. Kaul (1987) pointed out that if the monetary authority follows a procyclical monetary policy we can observe a positive relation between inflation and stock returns. Instead, a countercyclical monetary policy will cause a negative relationship. In fact, this negative dependence is significantly persistent during interest rate regimes than under money-supply regimes since central banks pursue strong countercyclical policies.

In the inflationary environment of the 1970s, researchers became interested in the question of whether or not common stocks are a good hedge against inflation. Contrary to the commonly held view, Lintner (1975), Bodie (1976), Jaffe and Mandelker (1976), Nelson (1976), Fama and Schwert (1977), Schwert (1981) found evidence that nominal stock returns and inflation were negatively correlated in post-war U.S. data. Ram and Spencer (1983) suggested that the negative relation can be explained by the different impact that the real activity has on those two variables. It acts procyclically with inflation and countercyclically with stock returns. According to the Fama (1981) proxy hypothesis the negative association found between stock returns and inflation is the result of two underlying relationships: (a) that between stock returns and expected economic activity; and (b) that between expected economic activity and inflation. A positive relationship between stock returns and expected economic activity is driven by the expectation of higher future dividends, while a negative relationship between expected activity and inflation follows from money demand effects.

There have also been additional theoretical attempts to explain the observed comovements between stock returns and inflation (e.g. Danthine and Donaldson (1986), Marshall (1992), Bakshi and Chen (1996)). An alternative
approach has been presented by Hess and Lee (1999). They investigated whether these relations can be explained as a combination of demand and supply disturbances. According to their empirical findings the relative importance of the two shocks determines the nature of the correlation between stock returns and inflation. The supply shocks, which reflect real output fluctuations cause a negative stock return-inflation relationship. The demand disturbances are mainly due to monetary shocks and produce a positive stock return-inflation relationship.

An one-directional nonlinear causality going from stock returns to inflation rates emphasizes the role of the stock market in the determination of trends in inflation rate that works as the transmission channel of monetary policy. The stock market channel is well described by Sellin (2001): “A change in the money supply leads investors to revalue the stock market. Because the value of a stock is given by the sum of discounted future dividends, an easing or tightening of monetary policy can affect stock prices through expected future earnings as well as through the rate at which they are discounted. Hence, an altered monetary policy stance will induce changes in investors’ financial wealth, which should have an effect on private consumption expenditure. Companies’ cost of capital will also change, which should affect real investment spending. The resulting shift in real activity will ultimately have an impact on inflation” (pp. 492-493).

This growing body of literature concentrating on the linear dependence between stock returns and inflation is restricted to one dimension of this relationship. Although the recent empirical evidence suggested the presence of complexities, to our knowledge a few only works have investigated the existence of a potential nonlinear stock returns–inflation relationship (Boyd, 2001, Kim, 2003, Liu et al., 2005, Maghyereh, 2006, Hristu-Varsakelis and Kyrtsou, 2008). In order to study in more depth the dynamic attributes of this puzzle we suggest a quite different framework where the primary goal is to explore the association between their underlying dynamics. The study of nonlinear intra- and inter-dependences in macroeconomic data is a subject of crucial importance since employing the same economic measure in two economies with linear and nonlinear underlying dynamics respectively can have widely divergent effects. Through the use of the Recurrence Quantification Analysis (Webber and Zbilut (1994)), the test for structural breaks of Bai and Perron (1998) and the test for nonlinear causality of Diks and Panchenko (2006), we find evidence in favour of negative nonlinear linkages between the inherent dynamics of inflation and stock returns.

The article is organised as follows. In Sections 2, 3 and 4 we present the Recurrence Quantification Analysis and the Bai and Perron and Diks and Panchenko tests respectively. Section 5 discusses the empirical findings and Section 6 concludes the paper.
2. Recurrence Quantification Analysis

Recurrence Quantification Analysis (RQA) is an extension of recurrence plots (RPs), first introduced by Eckmann et al. (1987). It is a relatively new analytical tool for the study of nonlinear dynamical systems developed by Webber and Zbilut (1994) and then applied to theoretical time series by Trulla et al. (1996) and Zbilut et al. (2000). RQA methodology can be summarised as follows: the embedding matrix corresponding to the studied series is constructed by the method of time delays. Thus, \( x_t^m = (x_t, x_{t+\tau}, \ldots, x_{t+(m-1)\rho}) \) are the artificial vectors, where \( t = 1, \ldots, T-(m-1)\rho \), \( T \) is the number of observations, \( m \) is the embedding dimension, and \( \rho \) is the time delay. Next, using a Euclidean norm, distances \( D \) in \( n \)-space between individual i-j pairs are calculated. A RP is a graphical representation of the distances matrix \( D_{i,j} \), by darkening the point at coordinates \((i,j)\) that corresponds to a distance value between i and j vectors lower than a predetermined critical radius \( \epsilon \). The plot is symmetric (\( D_{i,j} = D_{j,i} \)) and the main diagonal is always darkened (\( D_{i,j} = 0, i=j \)). The main feature of RPs is that if the series is fully deterministic, the system’s attractor will be revisited by the trajectory sometime in the future. In that case, the RP will show short line segments parallel to the main diagonal. If the time series is independent and identically distributed, then the RP will not display any kind of structure. Some examples of RP on the following well-known processes are presented in Figure 1.

1. A white noise: 
   
   \[ R_t = \epsilon_t \text{ with } \epsilon_t \sim N(0,1) \]

2. A NLMA model (Barnett et al., 1997):

   \[ R_t = \epsilon_t + 0.8 \epsilon_{t-1} \epsilon_{t-2} \]

3. A GARCH process (Barnett et al., 1997):

   \[ R_t = h_t^{1/2} \epsilon_t \text{ and } h_t = 1 + 0.1 R^2_{t-1} + 0.8 h_{t-1} \]

4. A Mackey-Glass-ARCH process (Kyrtou and Malliaris, 2009):

   \[ R_t = 2.1 \frac{R_{t-1}}{1 + R^2_{t-1}} - 0.05 R_{t-1} + \epsilon_t \text{ with } \epsilon_t \sim N(0, h_t) \text{ and } h_t = 0.2 + 0.6 \epsilon^2_{t-1} \]
Figure 1: Recurrence plots of simulated series
5. A chaotic Feigenbaum recursion (Barnett et al., 1997):

\[ R_t = 3.57R_{t-1}(1 - R_{t-1}) \]

6. A discrete deterministic Mackey-Glass equation (Kyrtsou and Malliaris, 2009):

\[ R_t = 2.1 \frac{R_{t-1}}{I + R_{t-1}^{30}} - 0.05R_{t-1}. \]

As one can see there is no clear distinction between the different RPs. When data with high level of noise or even complex underlying deterministic structures are used the method of recurrence plots can be proved insufficient since it gives results that are very difficult to be evaluated quantitatively. For this reason, RQA was developed to provide quantification of important aspects revealed through the plot. Thus, the number of contiguous diagonal points, which constitute line segments are tallied as a percent of recurrent points, i.e. %DET. We also calculate the Shannon entropy of line segment distributions (ENT). In general, entropy values are low within periodic windows (epochs), because all lines are of identical length. On the contrary, entropy values are high within chaotic (non-periodic) windows because there is a large diversity in diagonal line lengths. Some applications of the RQA to macroeconomic and financial time series can be found in Kyrtsou and Vorlow (2005), Strozzi et al. (2002), Belaire-Franch (2004), and Belaire-Franch et al. (2002). To help to the understanding of this new methodology we calculate the nonlinear tools of %DET and ENT on three stochastic processes from the above simulated data. The levels of determinism and entropy of these series of reference can be seen in Figure 2. As it is expected, significant high levels of determinism and entropy are only achieved for the Mackey-Glass-ARCH process which is a combination of nonlinear neglected and heteroskedastic dynamics. The RQA methodology seems to be powerful and able to detect nonlinear determinism even if it is mixed with high dimensional signals.
Figure 2: %DET and ENT of a white noise, GARCH and Mackey-Glass-ARCH processes.

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3. Bai and Perron test for structural breaks

In this section we will present the Bai and Perron (1998, 2001, 2003) econometric procedure that it used to test for infrequent structural breaks. Following Bai and Perron (2003) we regress our variable on a constant and then test for structural breaks in this constant. More specifically the following model with m breaks (m+1 regimes) is estimated:

\[ R_t = \beta_t + \varepsilon_t \]  

for \( t = T_{j-1} + 1, \ldots, T_j, j=1, \ldots, m+1 \), and where \( R_t \) is our stationary variable in period \( t \) and \( \beta_t \) is the mean variable in the \( j^{th} \) regime. The indices \( (T_1, \ldots, T_m) \) are break points, which are considered to be unknown (by conversion \( T_0 = 0 \) and \( T_{m+1} = T \)). Then the eq. (3.1) is estimated with the use of the least squares principle.

Bai and Perron consider a type of F-statistic given just below

\[ \text{Sup} F_T(b) = F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_b) \]

Where \( \hat{\lambda}_1, \ldots, \hat{\lambda}_b \) minimize the global sum of squared residuals \( S_T(T\lambda_i) \) with \( i = 1, \ldots, b \) (b corresponds to the detected breaks), under the restriction that \( (\hat{\lambda}_1, \ldots, \hat{\lambda}_b) \in \Lambda_\zeta \). \( \zeta \) is called the trimming parameter. In our application five breaks are taken with a trimming of 0.15 as it is recommended by Bai and Perron (2001). Bai and Perron (1998) build two statistics, named the double maximum statistics – Udmax and WDmax-, in the aim to test the null hypothesis of no breaks in the time series against the alternative for the presence of an unknown number of breaks given an upper bound M.

\[ UD_{\text{max}} = \max_{1 \leq m \leq M} \text{Sup} F_T(m) \]

Bai and Perron (1998) also consider a different set of weights such that the marginal p-values are equal across values of m. This version of the test is denoted as WDmax. Having identified at least one breakpoint, the number of breaks is chosen by specifying the null hypothesis of \( l \) breakpoint against the alternative hypothesis of \( l+1 \) breakpoints and conducting a sequence of \( \text{Sup} F(l+1|l) \) tests.

4. Diks and Panchenko test for nonlinear causality

The method for nonlinear Granger causality used here is the modified version of the Baek and Brock (1992) test which was developed by Hiemstra and Jones (1994) and lately modified by Diks and Panchenko (2006). The important
addition of the modified test is that it relaxes Baek and Brock’s assumption that the time series to which the test is applied are mutually independent, individually independent and identically distributed. Instead, it is possible that each series presents short-term temporal dependence.

To define nonlinear Granger causality, assume that there are two strictly stationary and weakly dependent time series \( \{X_t\} \) and \( \{Y_t\} \), \( t=1,2,...,T \). Denote the \( m \)-length lead vector of \( X_t \) by \( X_t^m \) and the \( L_x \)-length and \( L_y \)-length lag vectors of \( X_t \) and \( Y_t \), respectively. For given values of \( m, L_x, \) and \( L_y \geq 1 \) and for \( \epsilon > 0 \), \( Y \) does not strictly Granger-cause \( X \) if:

\[
\text{Pr}\left( \left\| X_t^m - X_t^m \right\| < \epsilon \mid \left\| X_{t-L_x}^L - X_{s-L_x}^L \right\| < \epsilon, \left\| Y_{t-L_y}^L - Y_{s-L_y}^L \right\| < \epsilon \right) = \frac{\text{Pr}\left( \left\| X_t^m - X_t^m \right\| < \epsilon \mid \left\| X_{t-L_x}^L - X_{s-L_x}^L \right\| < \epsilon \right)}{\text{Pr}\left( \left\| X_{t-L_x}^L - X_{s-L_x}^L \right\| < \epsilon \right)} \quad (4.1)
\]

where \( \text{Pr}(\cdot) \) denotes probability and \( \| \cdot \| \) denotes the maximum norm. The probability of the left side of eq. (4.1) is the conditional probability that two arbitrary \( m \)-length lead vectors of \( \{X_t\} \) are within a distance \( \epsilon \) of each other, given that the corresponding \( L_x \)-length lag vectors of \( \{X_t\} \) and \( L_y \)-length lag vectors of \( \{Y_t\} \) are within \( \epsilon \) of each other. A test based on eq. (4.1) can be implemented by writing it in terms of the corresponding ratios of joint probabilities:

\[
\frac{C_1(m + L_x, L_y, \epsilon)}{C_2(L_x, L_y, \epsilon)} = \frac{C_3(m + L_x, \epsilon)}{C_4(L_x, \epsilon)} \quad (4.2)
\]

where \( C_1, C_2, C_3, \) and \( C_4 \) are the correlation-integral estimates of the joint probabilities. Hiemstra and Jones (1994) discuss how to derive the joint probabilities and their corresponding correlation-integral estimators. Assuming that \( \{X_t\} \) and \( \{Y_t\} \) are strictly stationary, weakly dependent, and satisfy the mixing conditions of Denker and Keller (1983), if \( \{Y_t\} \) does not strictly Granger-cause \( \{X_t\} \), then:

\[
\sqrt{n} \left[ \frac{C_1(m + L_x, L_y, \epsilon, n)}{C_2(L_x, L_y, \epsilon, n)} - \frac{C_3(m + L_x, \epsilon, n)}{C_4(L_x, \epsilon, n)} \right] \rightarrow N(0, \sigma^2(m, L_x, L_y, \epsilon)) \quad (4.3)
\]

where \( n = T + 1 - m - \max(L_x, L_y) \). The consistent estimator of the variance \( \sigma^2(m, L_x, L_y, \epsilon) \) is given in Hiemstra and Jones (1994). However if we choose \( L_x = L_y = m = 1 \), condition (4.2) can be expressed in terms of ratios of joint distributions of \( (X_t, Y_t, X_{t+1}) \) i.e.:
\[
\frac{f_{x_t y_t x_{t+1}}(X_t, Y_{t}, X_{t+1})}{f_{x_t y_t}(X_t, Y_t)} - \frac{f_{x_t x_{t+1}}(X_t, X_{t+1})}{f_{x_t}(X_t)}
\] (4.4)

In a recent study, Diks and Panchenko (2006) argue that the Hiemstra and Jones (1994) test tends to reject too often under the null of no Granger causality, especially for small values of \( \varepsilon \). To avoid this problem Diks and Panchenko modified the null hypothesis as

\[
E \left[ \left( \frac{f_{x_t y_t x_{t+1}}(X_t, Y_{t}, X_{t+1})}{f_{x_t y_t}(X_t, Y_t)} - \frac{f_{x_t x_{t+1}}(X_t, X_{t+1})}{f_{x_t}(X_t)} \right) \times g(X_t, Y_t, X_{t+1}) \right] = 0
\]

where \( g(.) \) is a positive weight function defined as \( f_{x_t}^2(X_t) \). Based on the eq. (4.4) Diks and Panchenko reformulate the null hypothesis implying now:

\[
q \equiv E[f_{x_t y_t x_{t+1}}(.)f_{x_t}(.) - f_{x_t}(.)f_{x_t x_{t+1}}(.)] = 0 \quad (4.5)
\]

The test statistic is the sample version of eq. (4.5).

\[
T_n(\varepsilon) = \frac{n-1}{n(n-2)} \sum_{i} f_{x_t y_t x_{t+1}}(x_{it}, y_{it}, x_{it+1}) \tilde{f}_{x_t}(x_{it}) - \tilde{f}_{x_t y_t}(x_{it}, y_{it}) \tilde{f}_{x_t x_{t+1}}(x_{it}, x_{it+1})
\]

\( \tilde{f}_{z}(. \varepsilon) \) is a local density estimate of each \( d_{\varepsilon} \)-variate random vector (for further details see in Diks and Panchenko, 2006). For \( L_x = L_y = 1 \), and if the sequence of bandwidth \( \varepsilon_n = Cn^{\beta} \) where \( C > 0 \) and \( \beta \in (1/4, 1/3) \) then the test statistic in the above equation satisfies

\[
\sqrt{n} \left( \frac{T_n(\varepsilon_n) - q}{S_n} \right) \overset{d}{\rightarrow} N(0, 1)
\]

i.e. the test statistic is asymptotically distributed as \( N(0,1) \) where \( S_n \) is an estimator of the asymptotic variance of \( T_n(.) \).

5. **Empirical findings**

Data used here are monthly observations from 01/1960 to 07/2002 (511 obs.) for the US Costumer Price Index (Cpi), and the Dow Jones Stock Price Index (DJ). All data are not seasonally adjusted. For both methods, the log-differenced
Consumer Price Index – that gives the realized inflation rate- (dlcpi) and log-differenced real Dow Jones Index series (dlpsdj) are used. The calculation of the recurrence plots for both series reveals the presence of determinism (Figure 3). There is a pronounced structure in the plots. Obviously there are not only diagonal lines but also vertical and horizontal ones. The quantification of such findings is difficult. For this reason we proceed with RQA. A preliminary analysis of their dynamical behaviour in Kyrtou and Vorlow (2005) using RQA measures provided evidence that dlcpi and dlpsdj present high-dimensional complexity.

In Figure 4 the %DET and ENT are plotted versus the epoch (window) number. Values are computed from a 100 point window (epoch) which approximately corresponds to 10-year observations while data are shifted 10 points (almost 1 year) between epochs. Line definition is taken equal to the minimum possible value of 2 months. The choice of the embedding dimension DE, the time delay τ and the resolution parameter ε is of crucial importance since inaccurate values can lead to false indications of chaotic or random structure. Iwanski and Bradley (1998) relaxe the necessity for accurate embedding. Theil et al. (2004) show that with no embedding in recurrence plots, we can receive accurate and unbiased information on the complexity. So, following the above studies we adopt the strategy DE=τ=1.

Figure 3: Recurrence plots of inflation and stock returns series
Figure 4: %DET for (a) Consumer Price Index, and (b) Dow Jones Index, ENT for (c) Consumer Price Index, and (d) Dow Jones Index. RQA parameters: embedding dimension=delay = 1, line definition = 2 points, length of each epoch = 100 points, data shift = 10, radius $\varepsilon = 10$. 
As the level of noise of the time series under examination is unknown we choose a threshold level $\epsilon$ of the lower 10% of the maximum rescaled distance between all embedded vectors using a Euclidean norm (Webber and Zbilut, 1994). From a closer examination of the evolution of determinism and entropy in Figure 4 we gather some important characteristics:

1. During the first three regimes, high determinism is obtained for the inflation rate. However in the 4th regime the DET reaches low values. The DET of stock returns presents a dissimilar shape in its 1st and 2nd regimes (Figure 4a,b). The detected relationship reveals the existence of negative correlation between the underlying components of the US inflation rate and stock returns. The challenge here is to investigate if there are systematic dynamics driving the fluctuations of those two series. It is possible that inflation indirectly causes fluctuations in stock returns via real output movements, when supply shocks perturb the market. Rapach (2002) has shown using US market data that the 1970s slump in stock prices was not due to increases in trend inflation per se, but to the negative productivity shocks (oil price shocks). Lee (2010) found that in the post-war period of 1948-2007 the negative relation is driven primarily by aggregate supply shocks as for example is the increases in oil prices that results in higher inflation and lower stock prices. Analysing further oil-market dynamics Kilian and Park (2009) supported that demand shocks in such markets i.e. shocks to precautionary demand, will generate negative association between real stock returns and inflation. Kyrtsou and Labys (2006) showed that over the period 1970-2002 US commodity price increases give rise to inflationary phases. An oil shock can lead to inflationary pressures when Fed responds by creating inflation either intentionally to ease the sudden sharp in oil prices or accidently because of unsuccessful estimation of the dynamics caused by this shock. In that case the oil shock can distort information about how much money the economy needs. Therefore, even if none of the above situations arrive, prices may rise indirectly since other

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1 Shocks driven by changes in the precautionary demand for oil which rises the uncertainty about shortfalls of expected supply relative to expected demand.
commodities are oil-dependent. So, the shock can be multiplied through the economy and raise the prices of goods and services. In turn, commodity prices can be affected by changes in macroeconomic fundamentals. Kyrtsou (2008) identified the crude oil as the determinant factor of US inflation fluctuations. This bidirectional relationship is driven by a nonlinear positive feedback mechanism accentuating even small deviations from equilibrium prices. It is interesting to mention that commodity markets do not only display fluctuations reflecting demand and supply imbalances. They also support trading in futures and options whose prices fluctuate as much as stock prices. The transmission mechanism of information among these variables is agent-dependent meaning that the nature of expectation and the extent of speculation determine the way that shocks are propagated within the system.

2. The important deterministic structure that reaches its maximum at the 24\textsuperscript{th} epoch for cpi corresponding to 1984 (Figure 4a) and at the 32\textsuperscript{nd} epoch for psdj corresponding to 1992 (Figure 4b) is due to high complexity. The respective ENTs (Figure 4c,d) take big values. We remind that entropy values are low within periodic windows (epochs), and high within chaotic (non-periodic) windows. As it can be seen in Figure 5a, high variability in inflation rate has been detected from 1964 to 1984. During this period where agents experienced difficult situations such as the recession of 1969-1970 and 1973-1975 and the energy crisis of 1973 and 1979, the deterministic component of inflation raises (Figure 4a). This increase is followed by inherent complexity, since entropy raises as well (Figure 4c). Similar observations can be given for the Dow Jones returns series. More precisely, its determinism increases rapidly from 1984 to 1992 (Figure 4b). The highest variability is detected during the sub-period from 1986 to 1991 (Figure 5b) which encompasses the Black Monday in October 1987, the mini crash of 1989 with the collapse of the junk bond market, the oil price shock of 1990 and finally the economic recession of 1990-1991 caused by excessive corporate leverage and bank capital problems.
The graphical detection of inter-dependences between the inherent dynamics of inflation and stock returns series can be combined with the nonlinear causality testing procedure. To avoid false acceptances or rejections of causality caused by inappropriate filtering\(^2\) we perform a preliminary bleaching of data only when linear causal structures are detected (Table 1). The results in Table 2 lead to the conclusion that there is evidence for bidirectional nonlinear causality.

\(^2\) See Theiler and Eubank (1993) for bleaching problems when data present underlying nonlinearities.
between dlcpi and dlpsdj. This type of inter-dependence has been characterised by Ma and Kanas (2000) as dynamic nonlinearity.

Table 1: Linear Granger Causality Test

<table>
<thead>
<tr>
<th>CPI → PSDJ</th>
<th>PSDJ → CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>F-statistic</strong></td>
<td><strong>probability</strong></td>
</tr>
<tr>
<td><strong>Panel A: Entire Sample 1960-2002</strong></td>
<td></td>
</tr>
<tr>
<td>3.448</td>
<td>0.0325</td>
</tr>
<tr>
<td><strong>Panel B: 1st Sub-sample 1960- mid 1982</strong></td>
<td></td>
</tr>
<tr>
<td>1.372</td>
<td>0.255</td>
</tr>
<tr>
<td><strong>Panel C: 2nd Sub-sample mid 1982-2002</strong></td>
<td></td>
</tr>
<tr>
<td>2.032</td>
<td>0.155</td>
</tr>
</tbody>
</table>

* Underlined probability values indicate significance at the 5% level.

Table 2: Nonlinear Granger Causality Test

<table>
<thead>
<tr>
<th>CPI → PSDJ</th>
<th>PSDJ → CPI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>T-value</strong></td>
<td><strong>Probability</strong>*</td>
</tr>
<tr>
<td><strong>Panel A: Entire Sample 1960:01-2002:07</strong></td>
<td></td>
</tr>
<tr>
<td>m=2</td>
<td>2.236</td>
</tr>
<tr>
<td>(1.388)*</td>
<td>(0.0825)</td>
</tr>
<tr>
<td>m=3</td>
<td>2.199</td>
</tr>
<tr>
<td>(1.971)</td>
<td>(0.0243)</td>
</tr>
<tr>
<td>m=4</td>
<td>2.522</td>
</tr>
<tr>
<td>(2.275)</td>
<td>(0.0114)</td>
</tr>
<tr>
<td>m=5</td>
<td>2.272</td>
</tr>
<tr>
<td>(1.576)</td>
<td>(0.0574)</td>
</tr>
</tbody>
</table>

for ε=1.50 conclusion: bi-directional nonlinear causality

| **Panel B: 1st Sub-sample 1960:01- 1982:07** |
| m=2 | 1.574 | 0.0577 | 0.532 | 0.2974 |
| m=3 | 2.129 | 0.0166 | 1.391 | 0.08215 |
| m=4 | 2.063 | 0.0195 | 1.735 | 0.04139 |
| m=5 | 2.372 | 0.00884 | 1.515 | 0.06484 |

for ε=1.50 conclusion: bi-directional nonlinear causality

| **Panel C: 2nd Sub-sample 1982:08-2002:07** |
| m=2 | 0.700 | 0.2418 | 1.717 | 0.0431 |
| m=3 | 0.979 | 0.1638 | 1.619 | 0.0527 |
| m=4 | 0.813 | 0.341 | 1.417 | 0.0782 |
| m=5 | 0.906 | 0.1823 | 0.813 | 0.2081 |

for ε=1.50 conclusion: unidirectional nonlinear causality from psdj to cpi

* Underlined probability values indicate significance at the 5% or 10% level.
* Within parentheses are reported the T-values and the respective probabilities when the residuals of a VaR(2) are used.

One of the potential sources of nonlinearity is the presence of structural change in an economic system. Table 3 presents the results of the Bai and Perron (1998) test. It reports the values and statistical significance of the SupF_T(m), the SupF(l+1/l), and the double maximum test (UDmax and WDmax). For dlcpi both
double maximum statistics are significant. On the contrary for dlpsdj only the UDmax test gives significant results. The significance of the SupF_T(m) test suggests that at least one break exists. Concerning the SupF(l+1|l) test only the SupF(2|1) and SupF(3|2) statistics are significant indicating the presence of 3 breaks (4 regimes) for inflation and 1 break (2 regimes) for Dow Jones.

Table 3: Bai and Perron Test for Structural Breaks

<table>
<thead>
<tr>
<th>Statistics</th>
<th>CPI</th>
<th>PSDJ</th>
</tr>
</thead>
<tbody>
<tr>
<td>SupF(1)</td>
<td>54.802*</td>
<td>7.57*</td>
</tr>
<tr>
<td>SupF(2)</td>
<td>52.764*</td>
<td>4.901</td>
</tr>
<tr>
<td>SupF(3)</td>
<td>57.472*</td>
<td>3.323</td>
</tr>
<tr>
<td>SupF(4)</td>
<td>44.993*</td>
<td>2.594</td>
</tr>
<tr>
<td>SupF(5)</td>
<td>35.997*</td>
<td>2.148</td>
</tr>
<tr>
<td>UDmax</td>
<td>57.472*</td>
<td>7.57*</td>
</tr>
<tr>
<td>WDmax</td>
<td>82.737*</td>
<td>7.57</td>
</tr>
<tr>
<td>SupF(2</td>
<td>1)</td>
<td>49.083*</td>
</tr>
<tr>
<td>SupF(3</td>
<td>2)</td>
<td>49.157*</td>
</tr>
<tr>
<td>SupF(4</td>
<td>3)</td>
<td>6.054</td>
</tr>
<tr>
<td>SupF(5</td>
<td>4)</td>
<td>0.103</td>
</tr>
</tbody>
</table>

Sequential Procedure

<table>
<thead>
<tr>
<th>Date of breaks</th>
<th>1967:04 (point 87)</th>
<th>1973:07 (point 164)</th>
<th>1982:07 (point 270)</th>
</tr>
</thead>
<tbody>
<tr>
<td>95% confidence intervals</td>
<td>1st break [75, 92]</td>
<td>2nd break [110, 169]</td>
<td>3rd break [266, 295]</td>
</tr>
</tbody>
</table>

* An asterisk indicates significance at the 5% or 10% level.

a The critical values for the supF tests at the 5% (10%) level are 8.58 (7.04), 7.22 (6.28), 5.96 (5.21), 4.99 (4.41), 3.91 (3.47) (for 5 breaks).

b The critical value for the UDmax test at the 5% (10%) level is 8.88 (7.46).

c The critical value for the WDmax test at the 5% (10%) level is 9.91 (8.20).

d The critical values of supF(l+1|l) (for l=1 to 5 breaks) at the 5% (10%) level are 8.58 (7.04), 10.13 (8.51), 11.14 (9.41), 11.83 (10.04), 12.25 (10.58).

In order to prevent misleading conclusions, we will attempt to reduce the effects of eventual breaks within the structure of the variables. On the basis of the common breakpoint (1982:07), we construct two sub-samples and then reapply the test of Diks and Panchenko (2006) for nonlinear causality. Hopefully, the results of the second and third panel of Table 2 confirm our assumption that structural change affects the inflation-stock returns relationship.

Indeed, the removal of the break changed the direction of causality in the second regime.

3 Due to the specific character of the detected nonlinearity over the sub-periods, Karagianni et al. 2010 called this remaining structure “break-released” nonlinearity.
Although quite often criticized by mainstream economics, the application of nonlinear tools in the aim to identify causal relationships between economic variables can provide information that the standard linear Granger causality methodology would miss. But more importantly, there is a deep economic reasoning beyond this type of empirical analysis. Nonlinearity and complexity in economic systems have been associated in a number of recent empirical works with noticeable inefficiencies of economic policies. Complex interactions between macroeconomic and financial variables are indeed a determinant factor of the observed fluctuations, the extent of various financial crises and the central bank reaction functions. Changes in asset prices related to non-fundamental factors such as poor regulatory practice and irrational behaviour of investors can have potentially significant impact on the rest of the economy. As Bernanke and Gertler (1989) pointed out, this effect can be highly nonlinear. Besides, the impact of changes in asset prices depends on the effects of credit-market frictions on the households, firms and financial intermediaries. Bernanke and Gertler (2000) explained this mechanism as a feedback movement that magnifies the dynamics introducing nonlinear structures. The extent of the effects of asset-price fluctuations will depend on the initial state of economic agents and financial institutions balance sheets. Similarly, Bierens (1997) argued that the nonlinear inflation-stock returns relationship might result from the presence of market frictions and transaction costs which can prevent agents from adjusting continuously the available information. Non-linearity is also induced by the inflation-related asymmetric adjustment. As it is shown by Boyd et al. (2001) the inflation-stock returns relationship depends on the evolution of inflation rate above or below a certain threshold. Besides, they find that sustained high rates of inflation can have adverse consequences on economic variables. Increases in inflation can intensify informational asymmetries in the market leading to less intermediary or stock activity. According to Hristu-Varsakelis and Kyrtsou (2008) nonlinear dynamics in the US inflation-stock returns relationship are induced by the asymmetric response of inflation to either positive or negative shocks in stock returns and vice versa (see also Kim, 2003).

The risk to mislead or ignore real dynamics by insisting on applying exclusively traditional linear tests could be shown with the simple presentation of the linear Granger causality test results in Table 1. As it can be seen in the whole sample linear unidirectional causality is achieved from dlcpi to dlpsdj. When the structural break is taken into account this causality disappears in both sub-samples. Besides, on the basis of the estimates of mean inflation and stock returns

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Contrary to the standard neoclassical assumptions, there are credit-market frictions, i.e. problems of information, incentives and enforcement in credit relationships. So, the cash flows and the conditions of balance sheets constitute determining factors of the agents’ ability to borrow and lend.
from the Bai and Perron (1998) procedure we can determine the linear association between them (Table 4).

Table 4: Estimates of the mean CPI and PSDJ for each regime

<table>
<thead>
<tr>
<th>Series</th>
<th>Regime 1</th>
<th>Regime 2</th>
<th>Regime 3</th>
<th>Regime 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI</td>
<td>0.0013</td>
<td>0.0041</td>
<td>0.0072</td>
<td>0.0025</td>
</tr>
<tr>
<td></td>
<td>(5.342)*</td>
<td>(14.814)</td>
<td>(31.014)</td>
<td>(16.447)</td>
</tr>
<tr>
<td>PSDJ</td>
<td>-0.0037</td>
<td>0.0073</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td></td>
<td>(-1.402)</td>
<td>(2.611)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* t-statistics are reported in parentheses.

Looking at the sign of the 4th estimate (4th regime) for inflation and the 2nd estimate (2nd regime) for stock returns we conclude in favour of a linear positive correlation during the second common sub-sample (i.e. after 1982:07). The application of the nonlinear VAR analysis proposed by Kyrtsou and Labys (2006, 2007) gives a new dimension on the relationship. We gain in realism and information by proceeding from simple linear considerations to more complicated nonlinear parameterizations.

Table 5: Estimation results for the bivariate noisy Mackey-Glass model

<table>
<thead>
<tr>
<th>Coefficients</th>
<th>Values</th>
<th>T-stat*</th>
</tr>
</thead>
<tbody>
<tr>
<td>α_11</td>
<td>0.1306</td>
<td>2.0423*</td>
</tr>
<tr>
<td>δ_11</td>
<td>0.6102</td>
<td>9.4641*</td>
</tr>
<tr>
<td>α_12</td>
<td>0.0055</td>
<td>1.7141*</td>
</tr>
<tr>
<td>δ_12</td>
<td>0.0066</td>
<td>2.0944*</td>
</tr>
<tr>
<td>α_21</td>
<td>2.0668</td>
<td>1.5579</td>
</tr>
<tr>
<td>δ_21</td>
<td>-0.1921</td>
<td>-0.1436</td>
</tr>
<tr>
<td>α_22</td>
<td>-0.002</td>
<td>-0.030</td>
</tr>
<tr>
<td>δ_22</td>
<td>0.0259</td>
<td>0.3976</td>
</tr>
</tbody>
</table>

An asterisk indicates significance at the 5% or 10% level. We used τ_1=τ_2=2, and c_1=c_2=2. The best delays have been chosen on the basis of likelihood ratio tests. The model we test is the following:

\[
X_t = \alpha_{11} \frac{X_{t-1}}{1 + X_{t-1}} - \delta_{11} \frac{X_{t-1}}{1 + Y_{t-1}} + \alpha_{12} \frac{Y_{t-1}}{1 + Y_{t-1}} - \delta_{12} Y_{t-1} + \epsilon_t
\]

\[
Y_t = \alpha_{21} \frac{X_{t-1}}{1 + X_{t-1}} - \delta_{21} \frac{X_{t-1}}{1 + Y_{t-1}} + \alpha_{22} \frac{Y_{t-1}}{1 + Y_{t-1}} - \delta_{22} Y_{t-1} + u_t
\]

Where \(X_t=dlcpi\) and \(Y_t=dlpsdj\) during the 2nd common regime. The feedback effect between dlpdj and dlcpi is measured by the simple sum of coefficients \(\alpha_{12}\) and \((-\delta_{12})\ i.e. \(\alpha_{12} - \delta_{12} = 0.0055 - 0.0066 = -0.0011\) (Kyrtsou and Labys, 2006, 2007).
As one can see in Table 5, a negative linkage is identified between stock returns and inflation. The direction of the mechanism completely reflects the graphical association between the inherent dynamics of inflation and stock returns. The nonlinear character of the relationship confirms the nonlinear Granger causality test results (Table 2).

6. Conclusions

An extensive analysis of underlying structures using the Recurrence Quantification Analysis showed that the inherent dynamics of the US inflation and Dow Jones Stock returns comove according to the chosen time period. Determinism and entropy of both series are negatively correlated over the first and second common regime. The application of Diks and Panchenko test validated the empirical findings of recent research in favour of nonlinear impact of inflation on stock returns movements and vice versa. The non-proportional character of nonlinearity reinforces uncertainty. As long as inter-dependences are complex and nonlinear, small perturbations in fundamentals can lead to unexpected propagations within the financial system.

Linking behavioural aspects of investors with fluctuations in real economy offers useful insights on the sources of imbalances in asset pricing and prolonged economic instability during financial distress. According to Verma and Soydemir (2009) individual investor sentiment can be related to inflation among other financial or no-financial factors. Moreover, as Brown and Cliff (2005) underline the investor sentiment may contain a combination of both rational and irrational and not necessarily only noise. So inflation acts as signal in the decision mechanism of the investor. Through this channel and taking into account that the trading of individual investors is systematic (Barber et al., 2009) the signal is transmitted and rapidly affects asset prices. This mechanism magnifies dynamics and by doing so it impacts nonlinearly stock returns.

The application of nonlinear methods appears interesting and quite attractive since solving the puzzle of endogenous dynamics can help researchers to quantify the effects of economic policy on the dynamic behaviour of macroeconomic and financial series. The importance of reconsidering the role of nonlinearity in macroeconomic and financial spheres has been emphasized by Kyrtsou and Labys (2006), who argue that in the presence of “... dynamic non-linearity between macroeconomic and financial variables, policy makers should reconsider their decisions. Comprehending such a complex structure between two or more such variables, policies focusing only on one economic variable are condemned to fail. On the contrary, multi-dimensional policies, i.e. policies that take into account a set of economic variables, can be more flexible and
consequently efficient, in the sense that they will have higher probabilities of minimizing deviations from their final policy objective”.

References


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