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# Conventional Nonlinear Relationships between GDP , Inflation and Stock Market Returns. An investigation for the Greek Economy.

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**Abstract**

One of the most enduring debates in economics is whether financial development causes in a linear or nonlinear manner, economic growth or whether it is a consequence of increased economic activity. Little research into this question has been done for the case of Greece especially in a nonlinear framework. This paper fills this gap by using simple nonlinearity tests to provide evidence of a positive and significant causal relationship going from stock market development to economic growth in Greece during the last 10 years.

**Keywords:** Economic growth, capital markets, non-linear causality tests.

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## 1. Introduction

The investigation of the effects of movements in the general price level of a stock market on the economic development of a country as well as the role of inflationary pressures on GDP growth are issues that have preoccupied and continue to be of interest to researchers of modern applied economics and policy makers alike.

In this paper we attempt an investigation of non-linear relationships between the changes of the real Gross Domestic Product of the Greek economy (GDP) on the one hand and the returns of the Greek stock market and the rate of inflation on the other.

Using quarterly data and simple statistical tests of linearity/ non-linearity, we are able to statistically verify the existence of non-linear effects of stock market returns and inflation on the determination of the real GDP of the Greek economy.

Next, we attempt to establish the direction of causality between the variables under examination. In order to investigate the existence and direction of causality we did not use the typical methods which are based on the use of models with different time lags to pinpoint the presence and direction of causality. As discussed in section 2 below, the typical causality tests distribute the effects among the economic variables involved and establish simplified causal relationships, often attributing causality in the presence of co-determination. In the methodological section (section 2) of this paper, we demonstrate, using simulated data, that in the presence of non-linearity the typical causality investigation models that use different time lags, often distribute the effects among the variables and identify at best simplified causality which is in fact due to the co-determination among the variables.

The paper proceeds as follows: Section 2 provides an overview of the methodology used, utilizing simulated data in order to xxx the choice of our model. Section 3 analyses the available data, while in section 4 we present the results of the empirical analysis. Finally, Section 5 contains the concluding remarks and implications for further research.

## 2. Methodology

The main goal of this study is to examine the existence of linear or non-linear effects from the stock market (say $x_{1t}$ ) and the rate of inflation (say $x_{2t}$) on the determination of the Gross Domestic Product (say $y_{\tau}$ ).

$$y_t = f(\, x_{1t}, x_{2t}, parameter) + \varepsilon_t \quad (1)$$

The basic test is to check whether the effects of the two dependent variables ($x_1$, $x_2$) on the dependent variable ($y$) are linear or non-linear, that is we will examine the form of the following relationships:

$$\frac{\vartheta y_t}{\vartheta x_{1t}} = \varphi_1\left(x_{1t}\right) \text{ και } \frac{\vartheta y_t}{\vartheta x_{2t}} = \varphi_2\left(x_{2t}\right) \qquad (2)$$

One basic assumption we make in our analysis is that there are no feed-back effects from the dependent variable (GDP) to the independent variables $x_{1t}$ and $x_{2t}$ . This is not an unrealistic assumption, given that our data are quarterly. The use of quarterly data is dictated by the fact that real GDP figures are not available for shorter periods [3]. Given this restriction, it is logical to assume that any feedback is exhausted within the quarter so that the best approach is to model the relationships among the variables in a static environment. However, this is not the only rationale for our approach, as shown in the following sections.

### *2.1 Causality test performance in the presence of non-linearity.*

The main reason, in our opinion, that justifies the use of a static model to test for linearity or non-linearity, is that the use of distributed lag models or criteria based on distributed lag specifications may often lead to non reliable conclusions on the ways that the economic variables under investigation are related. In the following section, with the use of simulated, “constructed” data, we test alternative methodologies used to establish causality and we are able to demonstrate that the use of distributed lag specifications may distribute the diachronic effects from the

[3] Stock market returns exist on a daily basis while inflation is available monthly

dependent variables in an arbitrary way, even though such effects were not present in the original series.

### *2.2. The Monte Carlo Experiments.*

Our simulation experiment is based on the following nonlinear in the variables and parameters '*true*' specification :

$$y_t = 3 + .34x^{0.45}{}_t + \varepsilon_t \tag{3}$$

$$\varepsilon_t \approx NID(.25)$$

Four exogenous variables were generated using the following processes:

$$x_t = \tau_i x_{t-1} + (\sqrt{(1-\tau_i)^2})w_t \qquad i = 1,2,3 \tag{4}$$

$$w_t \approx NID(.25)$$

with $\tau_1 = .1 \quad \tau_2 = .5$ and $\tau_3 = .95$ (5).

The values (5) of the parameters of the specification (4) were chosen to give different autoregressive characteristics on the data generating processes of the exogenous variables.

Experiments with independent variables with time trends were also undertaken. In this case we assumed that the independent variables were generated as follows:

$$x_{jt} = \exp(\beta_j TR_t) + \xi_{jt} \tag{6}$$

$$\xi_{jt} \approx NID(Uniform(.025,.25)) \;, \quad \beta_j \in Uniform(.001,.67)$$

and $TR_t = 1, 2, ....$ (Time Trend).

Using the simulated data generated with the help of relationships (3) to (6), we then apply the following tests:

*A. Non-linearity tests*

The non-linearity tests utilized in this study are based on the classic Wald test.

We test the hypothesis that

$$y_t = f(\, x_{1t}, x_{2t}, parameter) + \varepsilon_t$$

or more specifically,

$$y_t = \beta_0 + \beta_1 x_{1t}^{\gamma_1} + \beta_2 x_{2t}^{\gamma_2} + \varepsilon_t \qquad (7)$$

Against the hypotheses:

$$\left.\begin{array}{l} y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t}^{\gamma_2} + \varepsilon_t \rightarrow H_0 : \gamma_1 = 0, H_1 : \gamma_1 \neq 0 \\ y_t = \beta_0 + \beta_1 x_{1t}^{\gamma_1} + \beta_2 x_{2t} + \varepsilon_t \rightarrow H_0 : \gamma_2 = 0, H_1 : \gamma_1 \neq 0 \\ y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \varepsilon_t \rightarrow H_0 : \gamma_1 = \gamma_2 = o, H_1 : \gamma_1 \neq \gamma_2 \neq 0 \end{array}\right\} (8)$$

The testing of above hypotheses will be conducted using Wald's criterion, the application of which requires the estimation of non-linear model (7).

The estimation of the parameters of model (7) is based on the linearization (Taylor expansion) shown below:

Walds' test is applied on the model:

$$y_t - y_t^0 + \frac{\partial y_t}{\partial \beta_0}|_0 \beta_0^0 + \frac{\partial y_t}{\partial \beta_1}|_0 \beta_1^0 + \frac{\partial y_t}{\partial \beta_2}|_0 \beta_2^0 + \frac{\partial y_t}{\partial \gamma_1}|_0 \gamma_1^0 + \frac{\partial y_t}{\partial \gamma_2}|_0 \gamma_2^0 =$$

$$\frac{\partial y_t}{\partial \beta_0}|_0 \beta_0 + \frac{\partial y_t}{\partial \beta_1}|_0 \beta_1 + \frac{\partial y_t}{\partial \beta_2}|_0 \beta_2 + \frac{\partial y_t}{\partial \gamma_1}|_0 \gamma_1 + \frac{\partial y_t}{\partial \gamma_2}|_0 \gamma_2 + \varepsilon_t$$

Wald's test consists of the computation of the t statistic for each hypothesis of (8) as follows: $H_0 : \frac{\hat{\gamma}_1 - 1}{s_{\hat{\gamma}_1}} = 0 \quad H_0 : \frac{\hat{\gamma}_2 - 1}{s_{\hat{\gamma}_2}} = 0$

If it is proven that $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are statistically different from 1, then we prove the existence of non linearity such as (7).

*B. The Alternative Procedures: Testing Linear Granger Causality.*

In order to compare the performance of Wald's non-linearity test with the alternative methodology used for testing linear causality, we applied on our simulated data Hsiao's (1981) linear causality test. The test is based on a bivariate VAR representation for two stationary series $x_t$ and $y_t$. Hsio's sequential procedure for linear causality is based on the bivariate VAR representation

$$x_t = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_{x,t} \qquad (9)$$

$$y_t = \beta_0 + \sum_{i=1}^{n} \alpha_i x_{t-i} + \sum_{j=1}^{q} \beta_j y_{t-j} + \varepsilon_{y,t} \qquad (10)$$

where $x_t$ and $y_t$ are stationary variables and $n$ and $q$ are the lag lengths of $x_t$ and $y_t$ respectively. The null hypothesis in the Granger causality test is that $y_t$ does not cause $x_t$ which is represented by $H_0 : \beta_1 = \cdots \beta_q = 0$, and the alternative hypothesis is $H_1 : \beta_i \neq 0$ for at least one $j$ in Equation (9). The test statistic has a standard *F* distribution with (*n*, *T-n-q-1*) degrees of freedom, where T is the number of observations. Akaike Information Criterion is used to find the optimal lag lengths for both $x_t$ and $y_t$.

Hsiao (1981) has suggested a sequential procedure for causality testing that combines Akaike's final predictive error criterion (FPE) and the definition of Granger causality. To test for causality from $y_t$ to $x_t$ ,the procedure consists of the following steps:

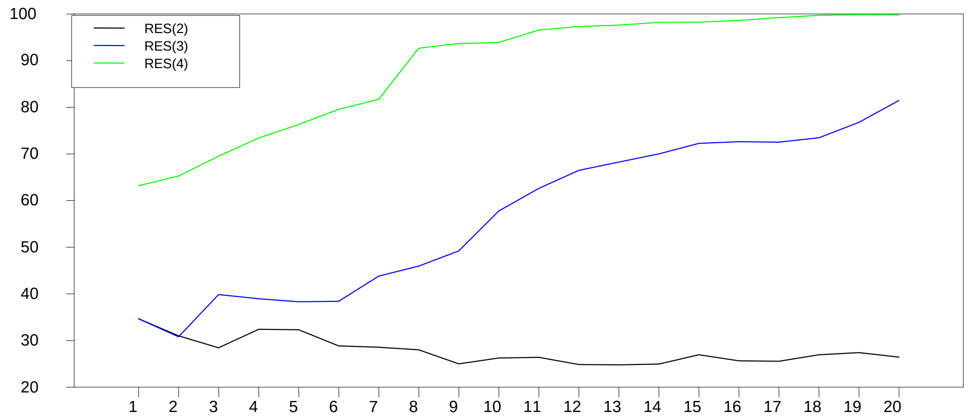
1. Treat $x_t$ as a one-dimensional process as represented by Eq. (1) with $\beta$j = 0 ∀j, and compute its FPE with $n$ varying from 1 to L, which is chosen arbitrarily. Choose the $n$ that gives the smallest FPE, denoted FPE_x($n$, 0).

2. Treat x as a controlled variable, with $n$ as chosen in step 1 and y as a manipulated variable as in Eq. (1). Compute the FPE's of Eq. (1) by varying the order of lags of $y_t$ from 1 to L and determine $q$, which gives true minimum FPE, denoted FPE_x($n$, $q$).

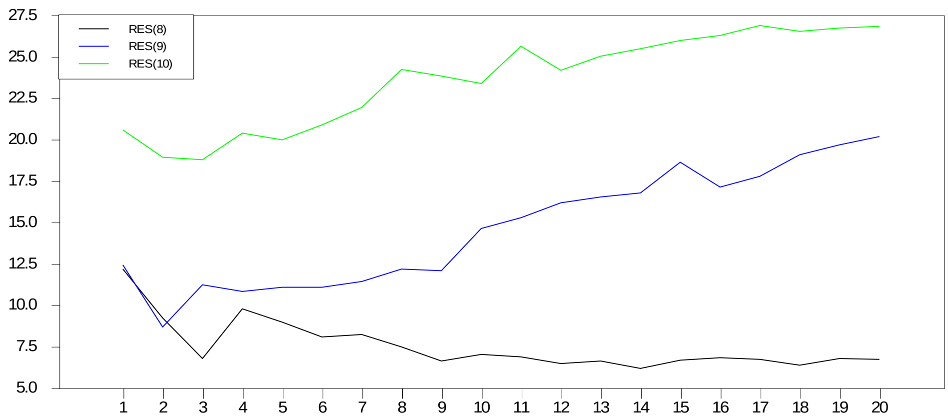
3. Compare FPE_x($n$, 0).) with FPE_x($n$, $q$). If the former is greater than the latter, then it can be concluded that $y_t$ causes $x_t$.

### *2.3 The Monte Carlo Simulation results.*

After a large number of data series were generated using the simulation model (3)-(6), we used them to calculate the non-linearity and causality tests, aiming to validate “ex post” the accuracy of these tests. The results of applying the non-linearity and linear causality tests on our simulated data are shown in graphs 1-4 below.[4] On the horizontal axis of each graph we display the number of observations of the independent variable, while on the vertical we represent the percentage of successful identification of causality from variable $x_t$ to variable $y_t$ ($x_t \rightarrow y_t$) and rejection of the hypothesis of feedback effects ($x_t \leftarrow y_t$) between the variables. The top line represents analogous results using Wald's criterion.

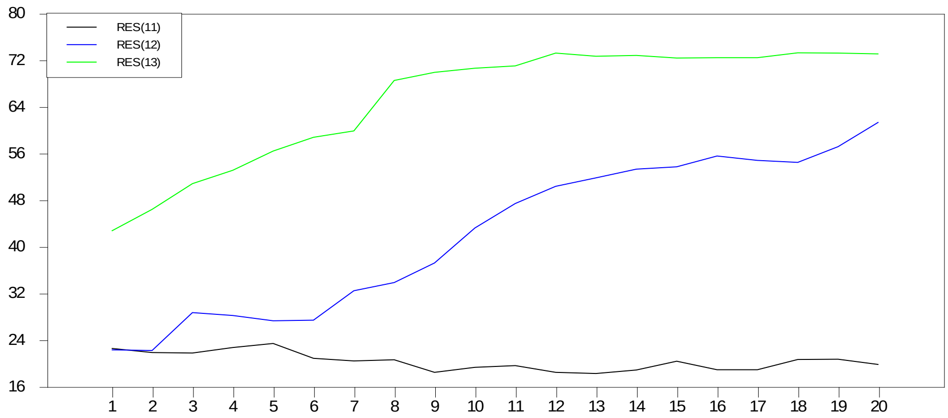



**Graph 1**. Percentage of successful identification of causality from $x_t \rightarrow y_t$ and rejection of the feedback from $y_t \rightarrow x_t$ for $\tau_1 = 0.1$

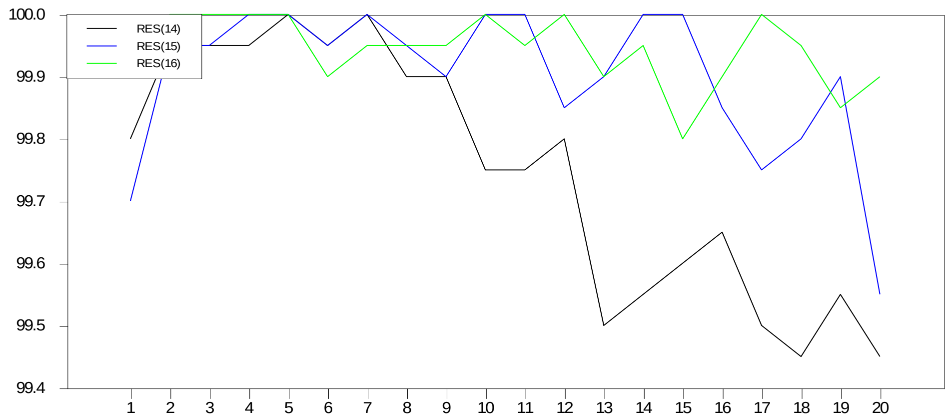



**Graph 2**. Percentage of successful identification of causality from $x_t \rightarrow y_t$ and rejection of the feedback from $y_t \rightarrow x_t$ for $\tau_2 = 0.5$

[4] Analytical numerical results of our experiments can be made available upon request to interested researchers.




**Graph 3**. Percentage of successful identification of causality from $x_t \rightarrow y_t$ and rejection of the feedback from $y_t \rightarrow x_t$ for $\tau_2 = 0.9$




**Graph 4**. Percentage of successful identification of causality from $x_t \rightarrow y_t$ and rejection of the feedback from $y_t \rightarrow x_t$ in the presence of time trends in $x_t$ (eq 6)

The results of our experiments are quite revealing: In graphs 1-3, the Wald test (top line) performs better than the linear causality test. In the cases where a static non-linear relationship exists by design, between $y_t$ and $x_t$, the application of Hsiao's linear causality test "distributes" the effect of $x_t$ diachronically. In the opposite case, the use of classic non-linearity successfully (99%) identifies a more representative rendering of their “true” relationship.

Another interesting observation comes from the analysis of the autocorrelation characteristics of independent variable $x_t$. As the autocorrelation coefficient $\tau_i$ approaches one, then the percentage of the successful identification of the relationship between the two variables decreases. Another observation is that as the number of observations increases, the probability of successful identification of the true relationship between the variables increases, except in the case of strong time trends in the exogenous variable.

## 3. The data used in the study.

The empirical analysis is carried out using quarterly data for the period 1984:Q1–2002:Q4 for Greece. The output variable is the real Gross Domestic Product (GDP), the price level is the consumer price index (CPI) and the stock market variable is the value of the Athens Stock Exchange General Index (STOCK). Domestic real stock returns (DLRSTOCK) is the difference between the continuously compounded return of the ASE General Index and the Greek inflation rate, which is calculated using the consumer price index. All data are taken from the Bulletin of Conjectural Indicators of the Bank of Greece, are not seasonally adjusted and can be found in the appendix.

For the application of the statistical tests for non-linearity in the relationships among the variables under investigation, the available data were first expressed in logarithms (LGDP, LRSTOCK, LCPI) and then their first differences were taken, due to presence of stationarity in the data.

## 4. The results

Using the above described data series, we first tested whether the relationship among the variables is non-linear,

$$y_t = \beta_0 + \beta_1 x_{1t}^{\gamma_1} + \beta_2 x_{2t}^{\gamma_2} + \varepsilon_t \qquad (7)$$

testing the following hypotheses:

$\mathrm{H}_0: \quad \hat{\gamma}_1 = 1$

$\mathrm{H}_0: \quad \hat{\gamma}_2 = 1$

$\mathrm{H}_0: \quad \hat{\gamma}_1 = \hat{\gamma}_2 = 1$

Applying Wald's criterion to the estimated parameters of (7), we concluded that:

$$\frac{\hat{\gamma}_1 - 1}{s_{\hat{\gamma}_1}} = \frac{1{,}186 - 1}{0{,}0116} = 14{,}25$$

$$\frac{\hat{\gamma}_2 - 1}{s_{\hat{\gamma}_2}} = \frac{2.01 - 1}{0.0317} = 13.12$$

As the values for the estimated parameters $\gamma_1$ and $\gamma_2$ are much higher than the value of the t-distribution , 1,96 for a large sample two-tailed test at the 5 percent significance level, we reject the null hypothesis of a linear relation between these three variables in favor of a nonlinear specification.

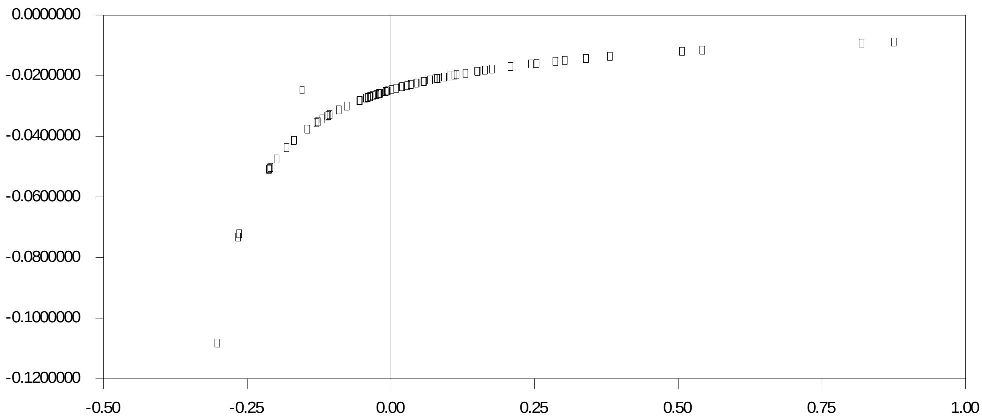
The presence of non-linearity in the effects from the two exogenous variables, $\chi_{1_\tau}$ and $\chi_{2_\tau}$ , that is the percentage changes in the value of ASE General Index and the changes in the Consumer Price Index (rate of inflation) on the evolution of the real GDP of the Greek Economy, is of significant importance. Non-linearity implies that the effects are very different in different ranges of the values of the variables.

In graphs Graphs 5 and 6 below we present these effects based on the estimated relationships:

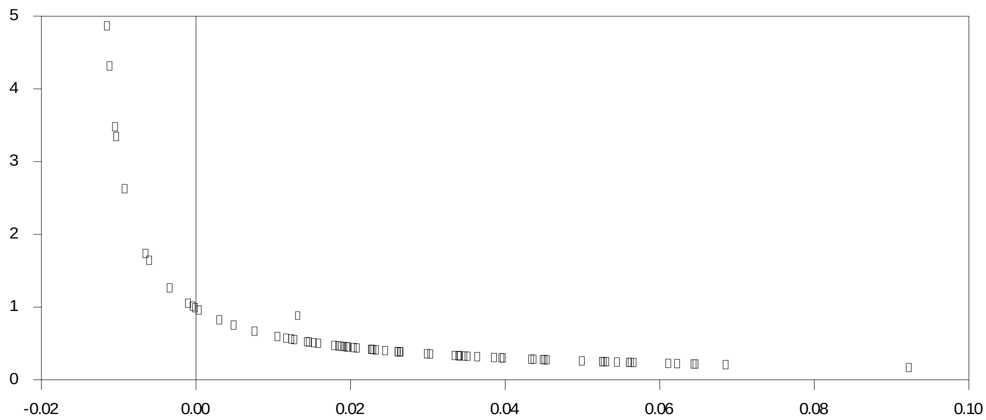
$$\frac{dy_t}{dx_{yt}} = \frac{d}{dx_{1t}} (\hat{\beta}_o + \hat{\beta}_1 x_{1t}^{\hat{\gamma}_1} + \hat{\beta}_2 x_{2t}^{\hat{\gamma}_2}) = \hat{\beta}_1 x_{1t}^{\hat{\gamma}_1} \ln(x_{1t})$$

and

$$\frac{dy_t}{dx_{yt}} = \frac{d}{dx_{2t}} (\hat{\beta}_o + \hat{\beta}_1 x_{1t}^{\hat{\gamma}_1} + \hat{\beta}_2 x_{2t}^{\hat{\gamma}_2}) = \hat{\beta}_1 x_{2t}^{\hat{\gamma}_1} \ln(x_{2t})$$




**Graph 5** The effect of changes in the value of the stock market index on the evolution of the Gross Domestic Product.




**Graph 6**: The effect of changes in the rate of inflation on the evolution of the Gross Domestic Product.

As can be seen in graph 5, the relationship between changes in the stock market value and the GDP is generally positive, as expected from theory and confirmed by a number of other studies, but the effect of the fluctuations in the stock market on real GDP is significantly different when the changes in the stock index are in the negative range, compared to the effects in the case of positive fluctuations. The shape of the curve shows that when the stock market is moving in negative grounds, any change in the index has a stronger effect on the real GDP compared to a bullish market, where a 1% fluctuation in the value of the index has a weaker effect on the real economy. Moreover, the effects become asymptotically zero as we approach positive values of real GDP growth.

Similarly, in graph 6 we observe that the overall effect of inflation on real GDP is negative, as expected from theory. Again, small changes in the inflation rate (around the vertical line) have a stronger negative impact on changes in real GDP whereas the effects are weaker, the higher the inflation rate. Here we use the actual inflation of the same period and we do not differentiate between anticipated and unanticipated inflation as do other studies focused on the subject. Nevertheless, the fact that non-linearity is present implies that the effects are different for different ranges of values of the variables under study.

## 5. Conclusions

This study contributes to the extensive literature that investigates the role of capital markets fluctuations and the rate of inflation on the real GDP. Using simple non-linearity tests we were able to demonstrate that for the Greek economy and the period under investigation, changes in the value of the stock market and in the rate of inflation affect the evolution of real GDP in a non-linear way. While the stock market has a positive effect on real GDP growth, this effect weakens the higher the stock market’s rate of change. Similarly for inflation, there is a negative relationship that becomes weaker the higher the rate of inflation.

The case of Greece, over the period 1984–2002, serves as an example in our empirical investigation. Greece is a country with less mature financial markets compared to other advanced economies. Over the last two decades, its financial system was liberalized at an accelerating pace and expanded considerably, while the fairly remarkable growth rates achieved by the Greek economy after the early 1990s enabled the country to enter the Euro zone in 2001. We think that the conclusions drawn could be useful for the analysis of other medium-sized economies, such as the Central and Eastern European countries, which have recently joined the European Union.

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