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# Testing for Granger Causality Between Stock Prices and Economic Growth.

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## **Abstract**

This paper has focused on the relationship between stock market prices and growth. A Granger-causality analysis has been carried out in order to assess whether there is any potential predictability power of one indicator for the other. The conclusion that can be drawn is that stock market prices can be used in order to predict growth, but the opposite it is not true.

# 1 Introduction

For years, practitioners have analyzed the relationship between the growth of a Nation (in GDP growth) and the stock market. In particular, the question about the forecasting power of the stock prices for the economic growth has been very debated.

Those who support the market power argue that the stock market contains information about the future economic growth. Thus, stock prices reflect expectations about profitability, and profitability is assumed to be linked with economic activities. If the economy is expected to go in to a growing phase the stock market will predict this, bidding up the prices of stock since future earnings are supposed to rise. Campbell (1989) relates stock market to real economy through the fundamental valuation of equity :

$$StockPrice = \sum_{j=1}^{\infty} \frac{ExpectedDividends_{t+j}}{(1+k)^j}$$

where  $k$  (assumed to be constant) is the rate at which the dividends are discounted. According to this equation it is possible to state that the stock prices are directly related to future profitability, that is supposed to be related with the real economy. Since this model gives great importance to expectations, it has to be considered that investors do not always anticipate correctly the returns. Thus sometimes the stock market will mislead the direction of the economy.

Another element that supports the stock market predictability is the "wealth effect". When the stock market rises, investors are willing to spend more because they are more wealthy, so the economy expands. On the other side if the stock prices declines, investors are less wealthy and spend less, so the economic growth decreases.

Summarizing, fundamental variation models and the wealth effect, both suggest that the stock market predicts economy, although it can be argued that the causations are different.

There are also critics to these theories. One of these is related to the expectations and the fact that they are subject to human error. Moreover Pearce (1983) and Campbell (1989) point out that the stock market has generated false signals in previous years, hence more evidence of this predictability capacity is needed.

This paper is structured as follows. Section 2 provides an overview of the methodology that has been used. In section 3 a description of the data and their preliminary analysis is presented. Section 4 reports the results of the empirical analysis. Section 5 concludes the paper.

## 2 Methodology

Granger (1969) proposed a time-series data based approach in order to determine causality. In the *Granger-sense*  $x$  is a cause of  $y$  if it is useful in forecasting  $y$ <sup>1</sup>. In this framework "useful" means that  $x$  is able to increase the accuracy of the prediction of  $y$  with respect to a forecast, considering only past values of  $y$ .

**Definition 1:** Assuming to have an information set  $\Omega_t$  with the form  $(x_t, \dots, x_{t-j}, y_t, \dots, y_{t-i})$ , we say that  $x_t$  is *Granger causal* for  $y_t$  wrt.  $\Omega_t$  if the variance of the optimal linear predictor of  $y_{t+h}$ , based on  $\Omega_t$ , has smaller variance than the optimal linear predictor of  $y_{t+h}$  based only on lagged values of  $y_t$ , for any  $h$ . Thus,  $x$  *Granger-causes*  $y$  if and only if  $\sigma_1^2(y_t : y_{t-j}, x_{t-i}) < \sigma_2^2(y_t : y_{t-j})$ , with  $j$  and  $i = 1, 2, 3, \dots, n$  and  $\sigma^2$  representing the variance of the forecast error.

There are three different types of situation in which a *Granger-causality* test can be applied:

- In a simple Granger-causality test there are two variables and their lags.
- In a multivariate Granger-causality test more than two variables are included, because it is supposed that more than one variable can influence the results.
- Finally Granger-causality can also be tested in a VAR framework, in this case the multivariate model is extended in order to test for the simultaneity of all included variables.

The empirical results presented in this paper are calculated within a simple Granger-causality test in order to test whether Stock prices "Granger cause" economic growth and vice versa.

Growth rate of real values of Standard and Poor's Composite index (SP) is used as an indicator for stock prices, while changes in economic growth are measured by the rate of growth of real GDP. Thus, according to Mahdavi and Sohrabian (1989), the following two equations can be specified

$$(GDP)_t = \alpha + \sum_{i=1}^m \beta_i (GDP)_{t-i} + \sum_{j=1}^n \tau_j (SP)_{t-j} + \mu_t \quad (1)$$

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<sup>1</sup>This idea is consistent with the notion that the cause precedes the effects but cannot be applied to the contemporaneous values of  $x$  and  $y$ .

$$(SP)_t = \theta + \sum_{i=1}^p \phi_i (SP)_{t-i} + \sum_{j=1}^q \psi_j (GDP)_{t-j} + \eta_t \quad (2)$$

Based on the estimated OLS coefficients for the equations (1) and (2) four different hypotheses about the relationship between GDP and SP can be formulated:

1. Unidirectional *Granger-causality* from SP to GDP. In this case Stock prices increase the prediction of the economy but not vice versa. Thus  $\sum_{j=1}^n \tau_j \neq 0$  and  $\sum_{j=1}^q \psi_j = 0$ .
2. Unidirectional *Granger-causality* from GDP to SP. In this case the growth rate of the economy increases the prediction of the Stock Prices but not vice versa. Thus  $\sum_{j=1}^n \tau_j = 0$  and  $\sum_{j=1}^q \psi_j \neq 0$ .
3. Bidirectional (or feedback) causality. In this case  $\sum_{j=1}^n \tau_j \neq 0$  and  $\sum_{j=1}^q \psi_j \neq 0$ , so in this case the growth rate of the economy increases the prediction of the Stock Prices and vice versa.
4. Independence between GDP and SP. In this case there is no *Granger-causality* in any direction, thus  $\sum_{j=1}^n \tau_j = 0$  and  $\sum_{j=1}^q \psi_j = 0$ .

Hence by obtaining one of these results it seems possible to detect the causality relationship between stock prices and the economic growth of a country.

### 3 Data Analysis

The totality of the data that we are going to analyze was taken from Econstats, from the Standard and Poor's website and from Datastream. The country that has been chosen for this empirical test has been the United States, with nominal values made real through the use of the Implicit GDP Price Deflator anchored to the year 2000. Standard's and Poor index has been chosen as the indicator of the stock market prices.

In this paper a wider range of data than the ones analyzed in previous papers in the literature has been used, and the time series are given all the way to the end of 2005. A quarterly frequency has been used, since it is the most logical given the need to observe changes in GDP over time. The two series, obtained in real values, have been manipulated to work with the growth ratios only.

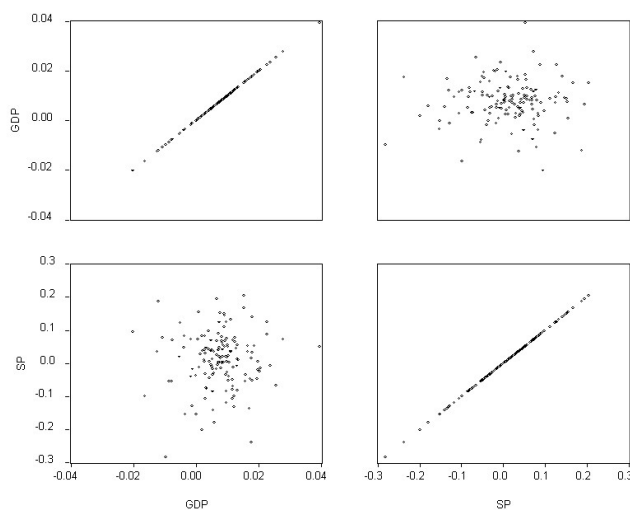


Figure 1: Scatter plots for GDP growth and SP growth

Figure 1 shows how just a quick view on the data can support a positive relation between the two variables (in percentages of growth). The analysis in this paper will show in formal terms what kind of relation can be hypothesized on these two variables.

## 4 Empirical Analysis and Results

The first step in this analysis concerns the stationarity of the GDP and SP series. Granger causality requires that the series have to be covariance stationary, so an Augmented Dickey-Fuller test has been calculated. For all of the series the null hypothesis  $H_0$  of non stationarity can be rejected at a 5% confidence level.

Then, since the Granger-causality test is very sensitive to the number of lags included in the regression, both the *Akaike (AIC)* and *Schwarz Information Criteria* have been used in order to find an appropriate number of lags.

After that these requirements have been satisfied, Granger-causality tests are computed. Taking equation (1) as an example, the two steps procedure in testing whether *SP* causes *GDP* is as follows.

1. *GDP* is regressed on its past values excluding *SP* in the regressors. This is called the restricted regression, from which we obtain the restricted sum of squared residuals.

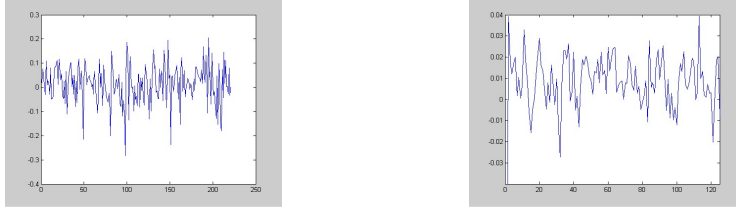


Figure 2: Plots of the GDP growth series on the right, and of the SP growth series on the left side.

2. Thus, a second regression is computed including the lagged *SP*. This is called the unrestricted regression from which the unrestricted sum of squared residuals is obtained.

The statistics is defined as

$$F = \frac{\left[ \frac{(SSR_r - SSR_u)}{n} \right]}{\left[ \frac{SSR_u}{T - (m + n + 1)} \right]} \quad (3)$$

where  $SSR_r$  and  $SSR_u$  are the two sums of squared residuals related to the restricted and unrestricted form of the equation; the elements that form the degrees of freedom are  $T$ , that is the number of observations while  $n$  and  $m$  are the number of lags as it can be seen from (1). The same procedure is used in order to test for the inverse Granger-causality relation in (2).

It is important that the data are covariance stationary in order to perform any kind of such regression, given the key of interpretation that we are looking for. For this the ADF test has been performed. This is a classic choice in literature and very strong test against unit roots. It is worth emphasizing that the two series that we are working with are already growth patterns, therefore we expect them to be  $I(0)$ . The result reflects the  $I(0)$  state of the variables. It is also possible to see this result from the graphs above, that show the rates of growth of the two series. Indeed the plots show covariance stationary compatible eye patterns

Since the series are covariance stationary we can proceed to checking for the number of lags to input in the model. The Granger causality test is sensitive to this kind of formatting of the model, and it is therefore important to choose an information criterion to base the decision on the number of lags to apply to the two series in the regressions to follow. For this purpose

we have analyzed a large range of lags both for the  $\tau$  referring to the GDP and for the one referring to the Standard and Poor value. Many previous works use the criterions of Akaike and Schwarz to formulate these choices. The optimal values are  $m = 2$  and  $n = 7$  for  $m$  defined as the lag of the GDP series and  $n$  the lag applied for the SP series.

Thus, the results of Granger Causality for equations (1) and (2) are represented in table 1 and 2. The tables report the results corresponding to different regressions, in order to have a comparison of the different regressions outputs.

The values of  $F$  statistic suggest that  $SP$  Granger-causes  $GDP^2$ , and  $GDP$  does not cause  $SP$ . Thus, it can be argued that past values of  $SP$  contribute to the prediction of the present value of  $GDP$  even with past values of  $GDP$ . Moreover by the single regressions it can be showed that also with 5 lags much of the coefficients have positive sign and with an acceptable significance level. However it has to be taken in account that the level of  $R^2$  is low, reminding that past rates of "SP" could have a limited ability for the prediction of  $GDP$ .

For the equation (2) the associated  $F$  tests give the opposite result, in fact there seems to be no Granger-Causality from past values of  $GDP$  for future values of  $SP$ . It has to be noted that this holds for all the specifications tried, and so in this case the null hypothesis of no causality from  $GDP$  to  $SP$ . Moreover all the  $R^2$  are close to zero, and the F-ratios (that test for all the right-hand coefficients significance) are statistically insignificant.

Concluding our tests for granger causality reflects what showed and assessed in the theory. There seems not to be any causality from real economy to the stock prices. But an inverse Granger-causality seems to be possible even if the relationship does not seem to be so strong. Indeed this can be found in the current and past events, that showed more than once how the  $SP$  is not always in tune with the growth of the economy. However, to the extent that the variation in the stock prices can be seen as a leading indicator for the fluctuations of the aggregate output, there is a better chance for countercyclical policies to be adopted in advance.

## 5 Conclusions

The relationship between stock prices and growth has been a very debated topic in last years. This paper have tried to assess the possibility that one of the two variables could cause (in a Granger's sense) the other. The results

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<sup>2</sup>\*\*\*, \*\*, \* and \* indicate statistical significance at the 1%, 2,5%, 5% and 10% level



m	n	DW-Stat	F-Stat	$\overline{R}^2$	F-Ratio
2	1	2.118	5.573(1, 120) ***	0.119	6.215(3, 120) ****
2	2	2.037	11.015(2, 120) ****	0.210	9.127(4, 120) ****
2	3	1.958	7.983(3, 120) ****	0.223	7.733(5, 120) ****
2	4	1.884	5.555(4, 120) ****	0.216	6.119(6, 120) ****
2	5	1.958	3.885(5, 120) ****	0.224	5.398(7, 120) ****
2	6	2.007	3.272(6, 120) ****	0.230	4.801(8, 120) ****
2	7	2.004	3.043(7, 120) ****	0.240	4.458(9, 120) ****

Table 1: Results of Granger-Causality Tests Eq.1

p	q	DW-Stat	F-Stat	$\overline{R}^2$	F-Ratio
2	1	1.912	0.007(1, 120)	0.003	0.1612(3, 120)
2	2	1.928	0.647(2, 120)	0.0128	0.444(4, 120)
2	3	2.016	0.461(3, 120)	0.017	0.471(5, 120)
2	4	2.002	0.307(4, 120)	0.014	0.319(6, 120)
2	5	1.984	0.462(5, 120)	0.022	0.425(7, 120)
2	6	2.001	0.484(6, 120)	0.270	0.448(8, 120)
2	7	2.002	0.408(7, 120)	0.268	0.389(9, 120)

Table 2: Results of Granger-Causality Tests Eq.2

from a double steps procedure has evidenced that it can be reasonable to better investigate in the capacity of stock prices of predicting short and medium term macroeconomic growth. On the other side it can be concluded that growth is not a good indicator for predicting future stock market outcomes.

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