AN EXTENSION OF TIME SERIES TESTS TO PANEL DATA

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Abstract
In the financial field much of the data available is in panel form. Nevertheless, some researchers convert these data into indices in order to facilitate its use. Today, because of the availability of software programs, it is easier than in the past to handle panel data in those instances where its use is preferable to the use of indices. The objective of this paper is to analyze the long run equilibrium relationship between prices and fundamentals while proposing a very simple method of extending time series models to panel data. Although this method has multiple applications, here we are solely concerned with investigating the cointegrating relationship between prices and fundamentals. This method has several characteristics that make it appealing. First, it is simple to implement (efficient). Second, it is general in scope (can be applied to many tests). Third, it takes into account arbitrary correlations (for example, among firms). Fourth, it does not require making unrealistic assumptions (such as the assumption of independence among firms within the same market). Our results are supportive of Han's (1996) in that we do not find cointegration between fundamentals and prices.

Keywords
Panel data, index, time series, cointegration, fundamentals, prices, long-run equilibrium, extension time series models to panel data, meta analysis

INTRODUCTION

The main goal of this paper is to examine the long-run equilibrium (co-integrating) relationship between prices and fundamentals. We accomplish this objective by extending time series models, estimation and testing, to panel data models.

In statistics, there is an extensive literature about the combination of tests. Many of them assume independence and have been extensively used in meta analysis. Due to the fact that some of these studies try to combine tests from different countries, they have been criticized on the grounds that they are combining dissimilar things. Nevertheless, this literature is ideal for the panel data available to the financial researcher. That is because we are dealing with comparable data across individuals and time.

Even though the method proposed here can be applied to any time series tests, we are going to use this procedure to demonstrate how to extend unit root and cointegration tests to panel data. There are four main reasons why the methodology proposed here is interesting. First, it is simple to implement (efficient). Second, it is general in scope (can be applied to many tests). Third, it takes into account arbitrary correlations (for example, among firms). Fourth, it does not require making unrealistic assumptions (such as the assumption of independence among firms within the same market).

This paper is divided into five sections. The first one presents an introduction to the subject of market efficiency and bubbles. The second covers a brief literature review of the papers that have investigated bubbles, and some of the econometric literature that applies to our subject. The third describes our hypotheses, the data and methodology used in this study. The fourth introduces the results and the fifth section summarizes the conclusions.

Background

The Efficient Markets Theory (EMT) implies that changes in security prices result from changes in expectations due to new information about fundamentals becoming available to investors. The financial assets' price will change to reflect the expected variation in the sum of the discounted cash flows from the asset. However, if the price movement does not reflect changes in the asset's fundamentals, but rather reflects changes in market psychology or other circumstances unrelated to business conditions, the volatility may be due to a bubble. The bubble can be thought of as the component of the share price that is not justified by the market fundamentals. Therefore, when a stock price reflects the discounted value of future cash flows, the bubble portion of the price equals zero. Nevertheless, if an asset's price greatly differs from the value suggested by its fundamentals, the bubble component of the price will be relevant (Hardouvelis, 1988).

One could argue that bubbles are the result of structural problems in emerging markets, and that they do not exist in sophisticated and efficient markets, such as the one in the US. Nevertheless, the following are some of the major reasons proposed to explain the birth and continued existence of bubbles in any market:

(1) Traders may have difficulty formulating stable future price expectations (Porter and Smith, 1995).

(2) A bubble can arise because the self-fulfilling expectation of the price changes can drive prices, independently of market fundamentals (Flood and Garber, 1994).

(3) If prices have been increasing for a significant period, people may consider fundamentals irrelevant. That is because some investments in stocks can be made on the belief that some other speculator will purchase the same asset at higher prices (Galbraith, 1955).

In this paper, we analyze the question of whether bubbles exist in the US market. This issue has already been addressed before. Nevertheless, we do approach this matter in a novel manner. Specifically, first we determine if bubbles exist: when over the long-run security prices are not backed up by their fundamentals. In this pursue, we apply a methodology that allows us to look at the cointegration of the time series of prices and fundamentals on a per company basis for all the companies in the S&P500 that provide the necessary data. Then, we aggregate the results in a later step. Since the data has not been altered or manipulated to build indices, these results are a true representation of the relationships. Thus, we analyze the long-term equilibrium relationship between prices and fundamentals using panel data. This helps us in two ways: first it increases the power of the tests, and second it preserves the properties of the data.

In general, this paper proposes that, if financial assets are fairly priced, the assets' prices should be related to the assets' fundamentals. Nevertheless, we do not propose a specific definition of fundamentals. Instead, we make the assumptions specified below.

First, regardless of the precise definition of "fundamental value", we know that stock price changes have to be related to actual changes in company "revenues". The reason is that, over the long run, operating revenues are the only source from which any payments can be made, including dividend payments. Therefore, if expectations are formulated correctly on average, there has to be a relationship between prices and corporate revenues.

Second, we do not want to measure expectations. We have already proposed that forming the wrong expectations can lead to the creation of bubbles. Furthermore, one could possibly use expectations to justify any price changes (Capie, 1990). Thus, we observe realized earnings (rather than expectations) since we presume that, if agents form expectations correctly, over the long run, changes in realized earnings have to be close to changes in expected earnings, and both should be related to changes in prices.

Third, even though revenues are very important, as we explain below, other variables should equally be considered. For example, some industry specific variables are relevant in that they contribute to costs in a way that may interfere with a "less contaminated" measure of revenue growth. One such variable is "investment in research and development" (R&D). R&D may be a proxy for future growth in the technology and pharmaceutical industries, nevertheless, it results in a reduction of earnings before interest and taxes (EBIT). Our idea is to first capture actual revenues, that is without the effects of the capital structure, investment, or accounting decisions made by management or specific to some industries. In a second step, we examine the effect on prices of the variables investors may consider relevant in determining growth. Due to the fact that some analysts follow EBIT, others EBIT plus depreciation, and so on, we construct six different models. These models try to explain changes on stock prices on the basis of changes in proxies for "fundamentals". Therefore, the dependent variable is always quarterly stock prices. The independent variable of the most general model is quarterly EBIT. In subsequent models: depreciation, R&D, investment in net working capital, and capital investment are added back to EBIT. Also, in order to capture the effect of the capital structure of the corporation on the stock price, one of the models includes the debt-to-equity ratio.

In testing whether bubbles exist, we manage variables that reflect true fundamental values, these are accounting earnings and cash flows. Also, we work with panel data versus creating indices and weighted averages. Even though using panel data presents some econometric challenges, it does enlarge the sample size. Therefore, it allows us to obtain more information and increase the power of the findings. In addition, manipulating the data to create indices and weighted averages could obscure the interpretation of our results. In particular, treating cross-sectional data as time-series, sometimes changes the properties of the data itself. For example, corporate dividends are for the most part stationary. Nevertheless, when all dividend payments are added to create an index, dividends become a stochastic variable.

Co-integration is a time-series concept that we reconcile with the panel structure of our data. The main idea is to apply regularly used unit-root and co-integration tests, individually, on the time series of each company in the sample. Then, we combine these tests into a "market-wide" unit-root and co-integration test.

If we find that, in the long-run, a cointegrating relationship between prices and fundamental proxies exists, then we could confirm the long-run predictability of asset prices defended in much of the literature. On the other hand, if no cointegration was to be found, we can say that the fundamentals' proxies used in this study are not explanatory of financial asset prices.

Literature Review

In general, the bubble literature analyzes whether financial asset prices are determined by the assets' fundamentals. One method employed to investigate the relationship between prices and fundamentals (represented by either dividends or earnings) is to investigate the long-run equilibrium relationship between these two time series. By a long-run equilibrium relationship between two non-stationary variables we mean the potential co-integration of these series. Co-integration analysis seeks to answer the question of whether there exists some linear combination of two non-stationary variables that is stationary.

Hamilton and Whiteman (1985) and Diba and Grossman (1988) proposed tests based on the stationarity of properties of stock prices and dividends. The general idea behind these tests, is that one can assess whether changes in security prices are consistent with changes in market fundamentals by determining whether the growth rate in both is comparable. Security prices are proposed to have a bubble component if market fundamentals are growing at a slower rate than the price of the corresponding asset. The tests performed by Kleidon (1986), Campbell and Shiller (1987), and Diba and Grossman (1988) do not reject the hypothesis that prices conform to fundamentals. In particular, Campbell and Shiller (1987) and Diba and Grossman (1988) suggest that real stock prices and real dividends are cointegrated. In their opinion, the deviations of stock prices from market fundamentals can be attributed to variables that possess a stationary mean.

The problem with Diba and Grossman's (1988) findings is that, given the sample sizes, the stationarity tests may not have sufficient power to detect any possible rational bubble. In theory, one could generate a bubble with an explosive mean whose fluctuations in a finite sample could follow the behavior of a stationary bubble (West, 1987). Therefore, the key is to differentiate between bubbles that burst, with explosive conditional mean or bubbles that do not burst, with a stationary unconditional mean of zero. Charemza and Deadman (1995) propose that, unless rational and intrinsic bubbles are constrained to burst, these can exist and not be captured by the unit root tests.

Another version of this idea is attempted by Han (1996) who uses Canonical Cointegrating Regression to investigate the long-run relationship between prices and dividends. The present value model implies that the levels, or the log levels, of stock prices and dividends are cointegrated when there are no rational bubbles. The author examines both the deterministic and the stochastic components of the prices and dividends in order to determine the validity of the present value model. Nevertheless, his findings show that neither the levels nor the log levels of stock prices and dividends are cointegrated. Han (1996) concludes that rational bubbles may exist in the deterministic component of stock price.

Within the literature, there are several criticisms to the cointegration tests. The first is that dividends, when analyzed at the firm level, might be stationary. Nevertheless, when we group all dividends paid by the market to create an index, this time series might be non-stationary. Therefore, data manipulation may alter the properties of the data itself and, in consequence, the results might be difficult to interpret. In this paper we address this issue by using the actual market panel data.

Another criticism is that cointegration might lack the power to detect some types of bubbles. This could happen because of the characteristics of the bubbles themselves if they are stochastic, for example, or because of insufficient data available (a typical problem if one uses time series annual data).

In reference to the bubble characteristics, we try to get around this problem by using the null hypothesis of "no cointegration." Therefore, if stochastic bubbles were to exist, and we could not detect them, still this would not result in a rejection of the null. If we accept the null of no cointegration and there are "undetected" stochastic bubbles, this can only reinforce our findings. In reference to the sample size, we address this issue by using ten years of quarterly, panel data for all corporations within the S&P500 that make available the necessary information.

A major general criticism to all the research that has compared prices and fundamentals is that failing to reject the presence of a bubble cannot be strictly interpreted as proving the bubbles' existence. Rejection could be due to a specification problem with fundamentals, the assumptions made about the model (the definition and relation between fundamentals and prices), or the assumptions made about the time series properties of the fundamentals. These are joint tests of the no-bubble hypothesis (Flood and Garber, 1980) (Hamilton and Whiteman, 1985). In this study, we try to partially get around these issues by proposing the null of "no-cointegration," and by increasing the power of our tests as already explained.

Hypothesis, Data, and Methodology

Co-integration is a time-series concept that we want to reconcile with the panel structure of the data available for the market. Using the recent work of Maddala (1996) we propose unit root and co-integration tests for panel data. The main idea is to apply regularly used unit-root and co-integration tests separately on the time series of each company in the sample, and then combine these tests into a "market-wide" unit-root and co-integration test. In the process, we propose new tests and ways of combining them under minimal assumptions.

In order to run the models needed to test our hypothesis, we collect the data summarized and described in Tables 1 and 2. The initial sample consists of all the companies included in the S&P500 Index. The final sample for each model varies with the availability of the quarterly accounting data needed for the construction of the independent variables. All the data are obtained from the Compustat tapes.

The main criterion for the selection of the companies in the S&P500 is that they represent a large percentage of the stock exchange market in the US (approximately 80%). This representation allows us to generalize our findings. We realize that in selecting these corporations our sample is skewed towards the largest and better-known companies. The only case when the skewness of the data could be relevant, is if we accept our null hypothesis (H_0), which says that there is a long-run equilibrium relationship between prices and fundamentals, and try to generalize these findings to the whole market. Nevertheless, this problem can be addressed with a prudent generalization of the findings. On the other hand, the companies in the S&P500 should be the most accurately priced since the information relevant to their operations is widely available.

As already mentioned, we work with panel data. Even though using panel data presents some challenges, the findings provide more information. The main reason for using quarterly accounting data is the need to use a proxy for real earnings that reflects actual company growth, not expectations of earnings. These data are available quarterly and yearly. Quarterly data is deemed appropriate because corporate earnings are publicly announced each three months. At this time, the market reacts to the new information and adjusts expectations and prices accordingly. We could also utilize annual data. Nevertheless, this would reduce the sample size considerably and would prevent the use of some of the proxies. In addition, annual data would not pick up as many effects as the quarterly data. For a more extended analysis on the benefits of using quarterly data refer to Cornell and Landsman (1989).

To test our hypothesis we construct six different models. The dependent variable is always quarterly stock prices. In reference to the independent variables representing the fundamentals, we have two goals. One is to test if prices are related to our fundamental proxies and the other to determine which earnings related information is the most compounded into market-clearing prices.

Before constructing the models, the raw data is examined to determine the companies to be included in each sample. It is the availability of data that determines the final samples. Therefore, no two models include the same companies or number of companies. In addition, the "Capital Investment" data can not be used as provided by Compustat. The reason is that their information is cumulative. For example, the first quarter presents three months of information, the second quarter presents six months, the third quarter nine months, and the fourth twelve months. The problem is solved by subtracting the first quarter from the second, the second from the third, and the third from the fourth.

After we resolve the problem with the Capital Investment data, we construct different proxies for fundamentals. The most general model is quarterly EBIT. In subsequent models depreciation, R&D, investment in net working capital, and capital investment are added back to EBIT. One of the models compares prices to the debt-to-equity ratio to capture the effect on the stock price of any changes in the capital structure of the corporation.

TABLE 1
Models to test our hypothesis

Model #	Years # Observations # Companies	Dependent Variable	Independent Variables	
1	1988-1998 9424 230	P= price		$DE = \frac{D_{it}}{E_{it}}$
3	1988-1998 7016 172	P= price	$R = EBIT_{it} + Depreciation_{it}$	
5	1989-1998 4255 115	P= price	$R = EBIT_{it} + Depreciation_{it} + NWC_{it} + Capital\ investment_{it}$	
6	1993-1998 900 45	P= price	$R = EBIT_{it} + Depreciation_{it} + NWC_{it} + R\&D_{it} + Capital\ investment_{it}$	
8	1988-1998 10147 249	P= price	$R = EBIT_{it}$	
12	1989-1998 11280 305	P= price	$R = FCF_{it}$	

TABLE 2
Description of variables in models to test our hypothesis

Variable	**Description**
Price (P)	Closing stock price, quarterly.
EBIT	Pretax income, quarterly plus interest expense, quarterly.
Net Working Capital (NWC)	Current assets, quarterly minus current liabilities, quarterly.
Depreciation	Non-cash charges for obsolescence of and wear and tear on property, allocation of the current portion of capitalized expenditures, and depletion charges, quarterly.
Capital Investment	Cash outflows or the funds used for additions to the company's property, plant and equipment, quarterly.
R & D	All costs incurred that relate to the development of new products or services. This is only the company's contribution, quarterly.
Free Cash Flow	Operating activities net cash flow minus cash dividends minus capital expenditures, quarterly.
Debt (D)	Debt obligations due more than one year from the company's balance sheet date, quarterly

As already mentioned, the idea is to first capture changes in actual revenues without the effects of the capital structure, investment, or accounting decisions made by management or specific to some industries. Otherwise our measure of company growth would be contaminated and, in addition, it would be difficult to determine whether the results are due to changes in actual revenues or to some other variable to which the market may respond. In a second step, if we find any of these models to be explanatory of price changes, then we may be able to determine which accounting variables are the most followed by the market.

A complete description of all the data used to build each model to test our Hypothesis is presented in Table 1. The first column assigns a number to each model. The table shows that each model differs in the definition of R. The second column specifies the sample period in years and the number of observations included in that period. The third column describes the dependent variable, stock prices, which is the same for every test. The last two columns describe the independent variables, either different definitions of earnings (R) or the debt to equity ratio (DE). Table 2 provides a description of each item used to construct these variables.

The data of the initial sample is examined to exclude those corporations that do not provide the necessary information. Also, in order to ensure the time series quality of the sample, the raw data is reviewed to delete periods after or before missing observations.

Methodology

The data used in our tests is unbalanced panel data. A motivation behind the use of panel data is that by enlarging our sample size we obtain more information and increase the significance of our findings. This is particularly useful when the time series data available is limited, as is the case of some of the samples in our study. In addition, panel data allows us to control for individual specific effects that may be correlated with included variables in the specification of the model.

On the other hand, the same additional structure of the data that provides the benefits of increased power and improved analysis also creates challenges in that it dictates new ways of estimation and testing. Therefore, some of the methodology employed in this study is adapted to be used with panel data. How this is accomplished is explained within the next paragraphs.

The long-run equilibrium relationship between prices and two financial time series used as proxies for fundamentals are explored by means of unit roots and cointegration tests, which are adapted to the panel structure of our data.

By a long-run equilibrium relationship between two non-stationary variables we mean the potential co-integration of these series. Co-integration analysis seeks to answer the question of whether there exists some linear combination of two non-stationary variables that is stationary. The intuitive idea behind such a relation is that although each of the two variables follows a random walk (i.e., they separately never converge to a traditional equilibrium) they are tied together and can never drift far apart from each other. This, in turn, means that knowledge of the level of one of these variables provides information about the value of the other, although past values of each of them have no explanatory power about their corresponding present level. If, in the long-run, such a relationship between prices or the debt to equity ratio and earnings exists we ought to expect these series to be cointegrated and, therefore, confirm the long-run predictability of asset prices defended in much of the literature.

Here we introduce the methodology used to test these long-run equilibrium relationships. Section 1) discusses panel data unit root and cointegration tests, while section 2) covers the Bonferroni Inequality.

The purpose of this estimation is to determine whether there is a long-run linear equilibrium relationship between stock prices and earnings or capital structure. That is, if earnings and capital structure can be predictors for stock prices.

Our model is given by

$$P_{it} = X_{it}\beta + \varepsilon_{it}, \qquad (i = 1,\ldots,N,\ t = 1,\ldots,T) \qquad (1)$$

where

P_{it} is quarterly closing stock prices for firm i at time t.

X_{it} denotes a set of independent variables which are the proposed predictors of stock prices. In particular, X_{it} denotes, DE and R, as the case may be. The debt/equity ratio *(DE)* is used as a proxy for capital structure, which DE denotes quarterly debt/equity ratio for firm i at period t

The second independent variable R is a proxy for earnings. As previously mentioned we use several definitions of earnings:

A = EBIT

B = EBIT + Depreciation

C = EBIT + Depreciation + Investment in NWC + Capital Investments

D = EBIT + Depreciation + Investment in NWC + Capital Investments + Research and Development

E = FCF defined as operating activities net cash flow minus cash dividends minus capital expenditures.

The revenues or earnings, R, is represented by any of the above definitions A, B, C, D, or E.

Tests for Long-Run Predictability of Stock Prices

1) Panel Data Unit Root and Cointegration

Many pairs of economic time-series are expected to behave in a way such that they do not drift too far apart from each other. Cointegration can be thought of as an equilibrium relation between two unit root stochastic processes. Several cointegration tests have been developed for times series data but little work has been done to extend the methodologies to panel data. For the time series case, see for example Engle and Granger (1987), Johansen and Juselius (1990), Phillips-Perron (1988), and Dickey and Fuller (1979). For a summary, see Hamilton (1994, Ch. 19). In our study we use cointegration techniques to investigate the long-term relationship between stock prices, company earnings and the debt-to-equity ratio.

Banerjee (1993) stated that "an equilibrium relationship holds between two variables X and Y if the amount by which actual observations deviate from this equilibrium is a median-zero stationary process: the difference between actual and predicted values has a fixed distribution around zero. In an equilibrium system, this error term can neither grow systematically nor indefinitely. The error term should not diminish over time since it portrays the continuously affected economic variables. With the absence of shocks the error term would disappear." This stationary process is the statistical concept on which equilibrium is based. Two unit root processes are cointegrated if there exists a linear combination of them that is stationary. Unit root variables (non-stationary variables) are those in which the means and variances change over time.

A prerequisite for testing for cointegration is that all variables are nonstationary. Therefore, we begin our analysis by examining the order of integration of individual time series. Classical methods of estimation are based on the assumptions that means and variances are constants and not dependent upon time. However, unit root tests have shown that these assumptions are not followed by most macroeconomic time-series which may be characterized by common trends or unit roots. If the variables possess one unit root, then these variables are said to be integrated of order one I(1). Many time series are represented by first differences.

Traditional estimation procedures, such as OLS, give misleading information when approximating relationships with unit root variables. This problem (the spurious regression problem) is important. Since the mean and variance of unit root variables change over time, the statistics computed with traditional methods do not converge to their true values as the sample size increases. In this case the regression statistics become time-dependent violating one of the main assumptions of the traditional tests.

In many cases the bias that exists results in the inappropriate rejection of the null hypothesis.

In our study we cannot use variables expressed as percentage changes since these are stationary. Therefore, we use the levels themselves to test whether quarterly closing stock prices, earnings, and the debt-to-equity ratio contain unit roots. In this case we use the tests proposed by Engle-Granger (1987). A problem encountered in this study is that we use a panel data set and therefore traditional tests are not directly applicable. Panel data provide more complete information and increase the power of these tests by increasing the sample size. Im, Pesaran, and Shin (1996), and Maddala and Liu (1996) introduce a unit root test for panel data. Co integration may be thought of as a multivariate extension of unit root tests. Maddala and Liu (1996) discuss a unit root test for panel data. Our approach is to extend their methodology and develop a test for cointegration in panel data. The model they consider is given by:

$$y_{it} = \alpha_i y_{i,t-1} + \upsilon_i + \epsilon_{it}, \quad \text{for } i = 1,...,N,\ t = 1,...,T_i \tag{16}$$

where α_i is the individual specific slope and real parameter to be estimated from the data,

υ_i is the individual specific intercept

and

$\epsilon_{it} = \theta_t + u_{it}$,

where u_{it} is an iid error term and θ_t is time-specific common effect.

They wish to test the hypothesis

$H_0 : \alpha_1 = \alpha_2 = \ldots = \alpha_N = 1$

against the alternative

$H_1 : \alpha_1 = \alpha_2 = \ldots = \alpha_N < 1$

The procedure they propose is to run an individual unit root test for each company in the sample and get the *p*-value, P_i, associated with each such test. Assuming that these test are independent of each other, they propose combining these individual *p*-values using Pearson's p_λ statistic, given by

$$p_\lambda = -2 \sum_{i=1}^{N} \ln (P_i)$$

Under the null, the p_λ statistic is distributed as a chi-square random variable with $2N$ degrees of freedom (see Maddala, 1977, ch. 4, page 42, Rao, 1973, pages 168-169, and Fisher (1933)).

This is a unit root test and we shall have to adapt it for cointegration. We propose using the Engle-Granger test. Let y_t and x_t be two $I(1)$ i.e., non-stationary, time series. In the first step of the Engle-Granger Test, one estimates by OLS the following model

$$y_t = \alpha + \beta x_t + u_t$$

Under the null of no cointegration, the predicted errors, $\hat{u}_t$ are also nonstationary, while, if there is cointegration, $(\hat{u})_t$ is $I(0)$, i.e., stationary. In a seco nd step, the DF (Dickey Fuller) test is used to test the hypothesis H_0: $\rho = 1$, in the model

$$\hat{u}_t = \rho \hat{u}_{t-1} + \epsilon_{it}$$

We propose running an Engle-Granger test for each company in our panel and using the p-values, P_i, for each of these tests to construct the p_λ statistic given above. Our null hypothesis is

H_0: y_t and x_t are not cointegrated for all companies in the sample

against the alternative that they are indeed cointegrated.

To determine the appropriate number of lags used for u nit root estimation and cointegration testing, the Schwarz Information Criterion (SIC) (Schwarz, 1 978) was used. SIC is given by:

$$SIC(j) = l_j(\hat{\theta}_j) - 1/2 p_j \ln N$$

where $l_j(\hat{\theta}_j)$ is the log-likelihood corresponding to the j-th model

and p_j is the penalty term.

2) Bonferroni Inequality

The main assumption of the Fisher test is independence of the individual tests. Nevertheless, in our situation one should expect correlation among companies. The consequence is that the p-lambda statistic has an unknown distribution, not necessarily the chi-squared distribution. Dufour and Torres (1996) propose using a statistic based on the Bonferroni inequality (Alt, 1982) (Maddala and Wu, 1996). N ote that the hypothesis H_0: $\alpha_i = 1$ for all i, i=1, 2, …, N can be split into sub-hypotheses H_{0i} : α_i =

1 for all i, i=1, 2, …, N. H_0 is false if and only if any of the sub-hypotheses H_{0i} is false. In particular, if γ_i is the significance level used to test H_{0i} then, by the Bonferroni inequality, the significance level γ of the total hypothesis is bounded by

$$\gamma \leq \sum_{i=1}^{N} \gamma_i.$$

Dufour and Torres (1996) propose to use $\gamma_i = \gamma / N$.

The Bonferroni inequality is very restrictive. As a consequence, the significance level of the overall hypothesis, H_0, is less than that of the sub-hypotheses, H_{0i}. Particularly, as N increases one over-rejects the null. Therefore, it is necessary to pay attention to the true significance level of the overall test, γ, that results from selecting significance levels for the sub-hypotheses, γ_i. Some adjustments may be warranted on a per-case basis to make meaningful use of this test.

Results

a) Panel Data Unit Root and Cointegration

In this section we investigate the results of our tests using using cointegration techniques. If our null hypothesis (H_0) of no cointegration is accepted we will conclude that there is no long-run relationship between changes in prices and changes in company earnings or changes in the debt to equity ratio. On the other hand, a rejection of the null would imply that there is a long-run relationship between these variables. Such a finding should dispute the random-walk hypothesis, which does not allow for the long-run predictability of prices.

For each one of the models listed in Table 2, we follow the same three-step procedure:

1) The appropriate number of lags to be included in the model is determined by the Schwarz Criterion.

2) A unit root test is done to check for stationarity. The results are compared with the appropriate chi square to accept or reject the null hypothesis of unit root.

3) A cointegration test is done. The results are compared with the appropriate chi square to accept or reject the null hypothesis of no cointegration.

Table 3 presents the appropriate chi-square used to be compared with the resulting p_λ to accept or reject the null hypothesis. This statistic is provided for the different number of companies included in the sample and for three different levels of significance.

TABLE 3
Chi square values

	Number of companies in the sample, χ^2 2N					
	45	115	172	230 249 305		
Level	χ^2(a,90)	χ^2(a,230)	χ^2(a,344)	χ^2(a,460)	χ^2(a,498)	χ^2(a,610)
0.1	107.565	257.8788	378.0139	499.2744	538.8491	655.169
0.05	113.1452	266.3781	388.2508	511.0018	551.0225	668.5666
0.01	124.1162	282.8143	407.9435	533.4879	574.3453	694.1843

Table 4 presents the results of the unit root tests performed on the data and models described in Tables 1 and 2. The first column presents the test number that corresponds to the model numbers described on Table 1. The second, third and fourth columns list the different variables. For each test, the first row describes the appropriate lag found using the Schwarz Information Criterion. The second row provides the p_λ *statistic* found for the variables used in the specific test. The third row specifies whether we accept or reject the null hypothesis of unit root. In this case the p_λ found is compared to the appropriate chi-square value listed on Table 3. Not applicable (NA) is specified when the test does not include that variable.

The results presented in Table 4 show that we reject the hypothesis of unit root in several cases. The meaning is that those variables are stationary and the cointegration techniques cannot be applied for that model.

Even though, a priori, in the literature it is assumed that all accounting variables are non-stationary when measured over annual intervals (they will measure changes in the company size), this may not carry when we utilize quarterly data. There are several reasons why stationarity can be found in some of these variables. For example, in the first test, the debt to equity ratio is found to be stationary. It may be reasonable to expect that such would be the case since both variables, in general, should not vary dramatically from one quarter to the next. Nevertheless, in reference to this finding, Whittington and Tippett (1999) suggest that it is possible that an accounting ratio is stationary even if its numerator and denominator are non-stationary. An explanation is that some ratios may assume a linear proportionate or equilibrium relationship between the numerator and denominator. Changes in the value of the ratio can be expected to have similar properties to the residuals from a co-integrating regression.

TABLE 4
Unit root results for tests listed in table 2

Test Number: 1	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	1	NA	1
P_λ	183.46337	NA	762.22919
H_0 of unit root	Accept	NA	Reject
Test Number: 3	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	1	4	NA
P_λ	153.9756	341.03888	NA
H_0 of unit root	Accept	Accept	NA
Test Number: 5	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	6	7	NA
P_λ	92.223942	196.54236	NA
H_0 of unit root	Accept	Accept	NA
Test Number: 6	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	8	8	NA
P_λ	360.00357	291.69494	NA
H_0 of unit root	Reject	Reject	NA
Test Number: 8	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	5	5	NA
P_λ	157.03126	463.00	NA
H_0 of unit root	Accept	Accept	NA
Test Number: 12	Price (P)	Earnings (R)	Debt/Equity
Unit root lag:	1	1	NA
P_λ	226.49093	6264.4267	NA
H_0 of unit root	Accept	Reject	NA

In addition to the D/E ratio, other variables have also been found to be stationary. In the sixth test, stationarity is observed in both prices and earnings. A possible reason is the small sample size, both in terms of companies and average number of observations per company included in the models. Another explanation may also be the restrictive nature of the earnings definition in this test, which could result in stationarity. The last place where we reject the hypothesis of a unit root is in test number 12. In this case the earnings proxy also appears to be stationary. Again, here the definition of the earning variable may be the reason for this finding.

Table 5 provides the results for the cointegration tests performed in those cases where both variables were determined to be non-stationary. The first column specifies the test number, the second the appropriate lag found by applying the Schwarz Criterion, the third column the pi-lambda for the cointegration, and the fourth and last column the result of comparing the pi-lambda with the appropriate chi-square specified in Table 3.

TABLE 5
Cointegration Results

Test Number	Appropriate lag (SIC)	Cointegration P_λ	H_0 of no cointegration
3	5	258.08746	Accept
5	5	170.25254	Accept
8	5	256.99877	Accept

It may be interesting to point that in the three cases were the SIC was performed for the cointegration, the 5th lag was found to be the relevant lag. This could be interpreted as the result of the availability of yearly data during that period. Nevertheless, in all of the cases we accept the null hypothesis of no cointegration between quarterly prices and different definitions of earnings. This finding is consistent with the results obtained from the models trying to analyze the contemporaneous relationship between variables. It is apparent that variables, other than earnings as defined in this paper, are explanatory of stock prices or percentage returns for the companies in our sample.

Regarding the debt to equity independent variable, since this ratio is stationary and prices are not, even though cointegration techniques cannot be applied, this difference in stationarity indicates in itself lack of cointegration. In summary, both or contemporaneous and long-run tests indicate that changes in earnings (as defined by our proxies) and capital structure do not explain changes in prices.

b) Bonferroni Inequality Results

Even though the above findings seem conclusive, still we should examine these results a little bit closer. The null hypothesis assumes all the series are unit root processes. This could present a problem since a few series can tilt the conclusion either way. That is why we have chosen to examine all the p-values for each of the data sets in our sample. In that manner in addition to the summary statistic we can look at each company's statistic and make an informed decision of whether there are unit root and cointegration processes. As we shall see, there can be instances when a single outlier affects the results. This is due to the restrictiveness of the Bonferroni inequality test.

The table below presents a summary of the results obtained by using the Bonferroni inequality and compares these to the ones obtained by using the Fisher statistic.

The main purpose of using the Bonferroni inequality is to check the results obtained using the Fisher test in light of the possible correlation among companies (observations may not be cross-sectionally independent) (Roll, 1988). In Table 6 we present the findings for Tests 1, 3, 5, 6, 8, and 12. The rows above the panels indicate the test number, the number of companies in the specific test, the chi-squared value that was calculated in Table 3 (for the purpose of easing comparison of findings), and the Bonferroni Test (γ_i). The latter is obtained following Defour and Torres (1996), $\gamma_i = \gamma / N$. For example, in Test 1: .05/230 = .000217. The columns and rows in the panel immediately below are self-explanatory. They name the variables included in the test and the following information related to each of the variables. The Fisher's p_λ, which is compared to the chi-squared critical value to accept or reject the null of unit root. The smallest p–value, obtained by ranking the p-values of each company in the test, and used to accept or reject the null of unit root by comparing it to the Bonferroni Test (γ_i). This is the smallest value for which we can reject the null. For example, in the case of the Price variable in Model 1, we accept the null since the smallest p-value of this series is greater than the Bonferroni Test value. The next column is the P-value of the Bonferroni Test, while the last column states whether we accept or reject the null of unit root in light of the Bonferroni Test. The last panel groups the individual p-values in the ranges specified in the first row. This helps analyze the exact distribution of the p-values and determine whether results are driven by an outlier. The rows specify the count (number of observations within each range), and the percentage (the count divided by the total number of observations).

TABLE 6
Summary results of unit root tests using bonferroni inequality

Test 1, N= 230
Chi-squared Critical Value = 511.0018
Bonferroni Test (γ_i) = .000217

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	H_0: of unit root
Price	183.4634	.015044	1.00	Accept
D/E	762.2292	1.02E-15	0.00	Reject

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	0	5	4	16	16	21	30	22	36	80
%	0	.0217	.0173	.0695	.0695	.0913	.1304	.0956	.1565	.3478
D/E										
Count	10	14	18	42	40	55	33	8	5	5
%	.0434	.0608	.0782	.1826	.1739	.2391	.1434	.0347	.0217	.0217

Test 3, N= 172
Chi-squared Critical Value = 388.2508
Bonferroni Test (γ_i) = .000291

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	H_0: of unit root
Price	153.9756	.015044	1.00	Accept
Revenues	341.0389	5.93E-05	0.01	Reject*

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	0	4	3	14	12	22	21	17	27	52
%	0	0.0232	0.0174	0.0813	0.0697	0.1279	0.1220	0.0988	0.1569	0.3023
Revenues (B)										
Count	4	9	10	30	18	17	24	14	19	27
%	0.0232	0.0523	0.0581	0.1744	0.1046	0.0988	0.1395	0.0813	0.1104	0.1569

Test 5, N= 115
Chi-squared Critical Value = 266.3781
Bonferroni Test (γ_i) = .000435

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of unit root
Price	92.22394	.014092	1.00	Accept
Revenues	196.5424	.001955	0.22	Accept

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	0	4	1	9	7	9	10 4		27	44
%	0	0.0347	0.0086	0.0782	0.0608	0.0782	0.0869	0.0347	0.2347	0.3826
Revenues (C)										
Count	3	5	5	15	15	13	20	8	16	15
%	0.0260	0.0434	0.0434	0.1304	0.1304	0.1130	0.1739	0.0695	0.1391	0.1304

Test 6, N= 45
Chi-squared Critical Value = 113.1452
Bonferroni Test (γ_i) = .001111

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of unit root
Price	360.0031	5.65E-26	0.00	Reject
Revenues	291.6949	2.63E-25	0.00	Reject

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	6	0	0	1	1	0	4	4	11	18
%	0.1333	0	0	0.0222	0.0222	0	0.0888	0.0888	0.2444	0.4
Revenues (D)										
Count	6	2	0	3	3	4	7	2	5	13
%	0.1333	0.0444	0	0.0666	0.0666	0.0888	0.1555	0.0444	0.1111	0.2888

Test 8, N= 249
Chi-squared Critical Value = 551.0225
Bonferroni Test (γ_i) = .000201

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of unit root
Price	157.0313	.034085	1.00	Accept
Revenues	463.1253	3.41E-05	0.00	Reject*

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	0	1	0	23	17	22	28	8	61	89
%	0	0.4016	0	0.0923	0.0682	0.0883	0.1124	0.0321	0.2449	0.3574
Revenues (A)										
Count	5	6	19	41	39	32	36	11	31	29
%	0.0200	0.0240	0.0763	0.1646	0.1566	0.1285	0.1445	0.0441	0.1244	0.1164

Test 12, N= 305
Chi-squared Critical Value = 668.5666
Bonferroni Test (γ_i) = .000164

Variables	Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	H_0: of unit root
Price	226.4909	.005752	1.00	Accept
Revenues	6264.427	2.25E-30	0.00	Reject

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Price										
Count	1	2	7	21	28	27	33	19	53	114
%	0.0032	0.0065	0.0229	0.0688	0.0918	0.0885	0.1081	0.0622	0.173	0.373
Revenues (G)										
Count	217	32	12	30	8	1	4	0	0	1
%	0.7114	0.1049	0.0393	0.0983	0.0262	0.0032	0.0131	0	0	0.0032

*Inspection of the p-values shows that we reject due, exclusively, to one company and the restrictiveness of the test.
$H_0 : \alpha_i = 1, \forall_i$
H_A : at least one $\alpha_i < 1$

The reason why, in our paper, we first determine the existence of unit roots is that they are a prerequisite to cointegration. We can only perform the latter if both series are non-stationary, that is, they contain a unit root. In Tests 3 and 8, we have rejected the null of unit root for revenues. Nevertheless, upon inspection of the individual p-values, it has been found that rejection is solely due to a single outlier in each of the series. That is, one single company out of the sample sizes 172 and 249 respectively, presents stationary revenues. Therefore, we have chosen to ignore both outliers and run cointegration tests between these series.

In conclusion, we determine we can perform cointegration using the data sets of Tests 3, 5 and 8. The information presented in the summary of the results in Table 7 is similar to that in Table 6 except in that the results of the cointegration refer to the relationship between the variables and not to the variables themselves. The only difference to consider is that the null hypothesis (H_0) is of "no cointegration"; therefore, if we accept the null it implies that there is no cointegration between the series.

TABLE 7
Summary results of cointegration tests using the bonferroni inequality

Test 3, N= 172
Chi-squared Critical Value = 388.2508
Bonferroni Test (γ_i) = .0002907

Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of no cointegration
258.08746	.00003943	0.01	Reject*

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Count	1	2	8	26	30	30	25	15	24	11
%	0.0058	0.0116	0.0465	0.1511	0.1744	0.1744	0.1453	0.0872	0.1395	0.0639

Test 5, N= 115
Chi-squared Critical Value = 266.3781
Bonferroni Test (γ_i) = .00043478

Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of no cointegration
170.25254	.00373053	0.43	Accept

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Count	1	1	6	20	12	20	14	7	16	18
%	0.0086	0.0086	0.0521	0.1739	0.1043	0.1739	0.1217	0.0608	0.1391	0.1565

Test 8, N= 249
Chi-squared Critical Value = 551.0225
Bonferroni Test (γ_i) = .000201

Fisher's p-lambda	Smallest p-value	P-value of Bonferroni test (γ)	$H_{0:}$ of no cointegration
256.99877	.02504113	1.00	Accept

	[0,0.01]	(0.01,0.05]	(0.5,0.1]	(0.1,0.3]	(0.3,0.5]	(0.5,0.7)	[0.7,0.9)	[0.9,0.95)	[0.95,0.99)	[0.99,1]
Count	0	2	5	30	27	44	42	27	48	24
%	0	0.0080	0.0200	0.1204	0.1084	0.1767	0.1686	0.1084	0.1927	0.0963

*Inspection of the p-values shows that we reject due, exclusively, to one company and the restrictiveness of the test.

$H_0 : \forall_i \ \nexists$ cointegration
$H_A : \exists_i$ s.t. $\exists$ cointegration

The above results confirm our prior findings obtained using the Fisher test. It is clear that in the only case where we reject the null of no-cointegration our results are driven by a single outlier, as it is shown in the distribution of p-values. Therefore, we confirm that at least for the samples represented by Tests 3, 5, and 8 there is no cointegration between prices and revenues as previously defined and we reject our Hypothesis.

The above findings of the lack of cointegration between earnings proxies and prices are consistent with the findings of Han (1996). Han (1996) reported that neither the levels (comparable to our exercise) nor the log levels of stock prices and dividends (his proxy for fundamentals) are cointegrated. Therefore, he concluded that rational bubbles may exist in the deteministic component of stock price and cannot be eliminated by the cointegrating vector.

The absence of a long-run equilibrium relationship reported in this paper could be explained by the findings of Harris (1999), who proposes that the accuracy of analysts' long run earnings growth forecasts is low. The author reports that forecasts are significantly biased, with expected earnings growth exceeding actual earnings growth by approximately 7% per year. In addition, the author shows that 80% of the forecasting error is random and over half of the total forecast error arises from the deviations of individual firm growth from average industry growth. The main finding is that the accuracy of the forecasting varies substantially with the characteristics of the company being forecasted. It has also been proposed that the bias in efficiency in the analysts' long run forecasts are considerable more pronounced than in their short run and interim forecasts. The findings of Harris (1999) support the hypothesis that analyst's consensus long run earnings growth forecasts are indeed irrational if they are to be interpreted as optimal forecasts of future earnings growth. This idea is consistent with our argument that bubbles in the market can exist if, on average, forecasted earnings do not become realized earnings in the long run.

CONCLUSION

The long-run equilibrium relationship between fundamentals and prices has been examined by many. The results obtained from the previous tests do not provide overwhelming evidence of a major relationship between prices and different measures of earnings or the debt to equity ratio. These findings add to the literature related to two fundamental questions in finance. The first one is whether stock prices reflect companies' fundamentals, represented here by accounting earnings and cash flows. Our results suggest that, for the most part, they do not. The second issue refers to whether a specific capital structure (measured by changes in the debt to equity ratio) adds value (measured by the changes in stock prices) to the corporation. Our findings suggest that the market does not reward a specific capital structure.

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