FUNDAMENTALS VERSUS CONTAGION PROXIES TO EXPLAIN FINANCIAL ASSETS PRICE CHANGES

IE Working Paper DF8-111-I 06 / 05 / 2004

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Abstract

There is a general consensus that expected returns are notoriously difficult to predict for many reasons, including modeling and econometric problems. The bubble and contagion literature proposes fundamentals and contagion proxies as explanatory of financial asset's price changes. This paper uses mean and semiparametric methods to analyze the explanatory value of some of these variables. The goal of this study is to determine which variables have higher explanatory value as well as their differential impact throughout the distribution of returns. The findings suggest that none of the twelve different models used to proxy fundamentals have any explanatory value for price changes. The three models used to proxy contagion variables are found significant regardless of the methodology used: OLS, panel data or quantile regression. Also, in the three models, the effect of the independent variable is found to increase with the quantile.

Keywords

Bubbles, contagion, semiparametric methods, financial asset prices, panel data, quantile regression.

Depósito Legal: M-20073-2002 I.S.S.N.: 1579-4873

INTRODUCTION

One of the earliest and most enduring models of behavior of financial security prices is the Random Walk Hypothesis. In its essence, the Random Walk Hypothesis asserts that future steps or directions cannot be predicted on the basis of past information. Since economic agents are rational utility-maximizing individuals, a one-step allusion to mere "fundamental randomness" is not adequate to motivate the Random Walk Model as a model of economic behavior. Instead, economists like Paul Samuelson (1965) have claimed that in an informationally-efficient market current prices fully reflect all available information and incorporate the expectations of all market participants. Hence, conditional on today's information, any future price movement is purely random (i.e., unpredictable), making the Random Walk Model and the "fundamental randomness" associated with it, simply the consequence of profit-maximizing individuals competing in an informationally-efficient market. This elegant and conceptually simple construction has been widely used in economics and finance as a first approximation to the true process generating asset prices. Following these ideas, during the 1960s and 1970s, the general academic community believed that changes in stock prices were almost perfectly random. Nevertheless, this assumption has been challenged lately by findings of different market singularities such as the day-of-the-week effect, the January effect, the small-firm effect, and overreaction which cannot be explained under this model.

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 asset's price will change to reflect the expected change 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.

A bubble can be thought of as the component of the share price that is not reflecting market fundamentals. 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 its fundamental value, the bubble component will be greater than the fundamental value component (Hardouvelis, 1988).

The price volatility resulting from the bursting of a bubble is important because investors demand higher returns when there is higher risk. In addition, risk aversion reduces the pool of investors. The consequences of high volatility are investor distrust, higher cost of capital, a decline in stock prices because of the higher discount on future earnings, a reduction in the number of capital investment projects to be undertaken, and, in the worst case scenario, a slowdown of the economy. Extreme volatility also distorts capital investment and allocation, taking funds from productive assets into more speculative ones. In some cases, these crises transfer to other sectors of the economy and other countries. These deviations can increase the riskness of the financial assets and the markets where the assets are traded (Chirinko et al., 1996). Therefore, it is important to determine what information is transmitted and assimilated within financial markets to establish market-clearing prices.

One could argue that bubbles (if proven to exist) are the result of structural problems in emerging markets, but that they do not exist in sophisticated and efficient markets such as 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 when an asset's market price depends positively on its own expected rate of change. That is because the self-fulfilling expectation of the price changes can drive prices independently of market fundamentals (Flood and Garber, 1994). (3) According to the "greater fool theory," people may consider fundamentals irrelevant if prices have been increasing for a significant period. This theory holds that some investments in stocks are made on the belief that some other "fool" will purchase the same asset at higher prices (Galbraith, 1955).

Another factor to consider is that, even though long-term movements in security prices may reflect changes in fundamentals, short-term variability could have other causes (DeLong, Shleifer, Summers, and Waldman, 1990). For example, traders may need to free some money for other uses (Wemers, 1999) or they may need to prove their skills to justify a high salary and authority to manage a large portfolio (Froot, Scharfstein, and Stein, 1992), institutional investors may share an aversion to stocks with certain characteristics, or they may disregard their private information due to the reputational risk of acting differently from other managers (Scharfstein and Stein, 1990). This last motivation could partially explain the current price growth of some internet stocks. Different groups of financial analysts and the financial press have hypothesized that in many cases the high values of internet stocks with negative or small current earnings could be attributed to a bubble.

An inefficiency created by short-horizon speculation is that traders may focus on poor quality data or on variables unrelated to fundamentals. Therefore, if speculators have short-term horizons, they may herd on the same information instead of trading on the underlying fundamentals. The resulting market-clearing prices could then deviate from those justified by the assets' fundamentals.

The primary goal of this study is to determine whether bubbles, as defined here, exist in the US market. That is whether fundamentals are explanatory of price changes. Because much of the literature points to contagion of opinion that results in herding behavior among agents as one of the causes for the creation of bubbles, we also examine the contemporaneous relationship between prices and proxies for herding behavior.

This paper proposes that, if financial assets are fairly priced (in accordance to their fundamentals), by extension, changes in the asset's prices should be related to changes in fundamentals. In this study, we do not propose a specific definition of fundamentals. Instead we make several assumptions. For example, regardless of the precise definition of fundamental values, we know that stock price changes have to be related to actual changes in company "revenues". In 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 changes in prices and changes in 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). Therefore, we rather observe realized earnings since we presume that, if agents form expectations correctly, in 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, revenues are important but other variables have to be considered. If changes in operating costs are higher than changes in operating revenues the net effect is negative. In addition, other 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. For example, investment in research and development (R&D) which may be a proxy for future growth in the technology and pharmaceutical industries, results in a reduction of earnings before interest and taxes (EBIT). Therefore, we construct twelve different models. The dependent variable is always changes in quarterly stock prices. The independent variable of the most general model is changes in quarterly EBIT. In subsequent models depreciation, R&D, investment in net working capital, and capital investment are added back to EBIT. Five of these models also include the debt-to-equity ratio to capture the effect on the stock price of any changes in the capital structure of the corporation. In addition to these twelve models, we create three additional models using monthly data to determine the predictability power of the herding behavior proxies. Again, the dependent variable is always changes in prices while the independent variables reflect money flows, volume, and volatility.

In testing for the existence of bubbles we separate the concepts of bubbles and contagion. It is convenient to analyze them separately because the existence of one does not imply the existence of the other. There can be bubbles in the economy without contagion and vice versa. This separation allows us to better interpret our findings and determine whether contagion or fundamental pries have greater explanatory value.

Also, we work with panel data (cross section and time series) versus creating indices and weighted averages. Even though using panel data presents some econometric challenges, it enlarges the sample size allowing us to obtain more information and increase the significance of our findings.

We are interested in exploring potential short-run predictability of asset prices by means of traditional conditional mean models such as OLS and panel data analysis, as well as the semiparametric method of quantile regression. Given the panel structure of our data, we perform OLS as well as Fixed, Between and Random Effects estimation. OLS is used as a benchmark model since it assumes that prices across companies and time are identically and independently distributed, a clearly unreasonable assumption. Fixed, Between and Random Effects models take into account potential heterogeneity across time and companies.

Quantile regression provides a complete picture of the distribution of prices conditional on the explanatory variables, and therefore, allows us to assess the impact of these variables on different parts of the return distribution. The idea behind quantile regression is that a particular explanatory variable may have different effects on different parts of the distribution of the explained variable. For example, it may be in significant in predicting the median return but very significant in some other quantile. Specifically, in this study, we could expect to find that fundamental variables (like debt to equity ratio and earnings) have a statistically significant positive coefficient on all quantiles but the highest. The interpretation is that fundamental variables have explanatory power for most changes in prices other than those we hypothesize to be related to the bubble. On the other hand, we can expect the proxies for herding behavior (like volume) to be significant in explaining only away from the median quantiles. This means that fundamentals affect share prices when below or around its median valuation, but have no effect at high quantiles. At these high quantiles the non-fundamental variables have explanatory power, with the most significance at the highest quantiles. If these asymmetric effects are found, they could be interpreted as evidence that when a bubble has formed, fundamentals are not relevant but non-fundamentals are, while fundamentals are important when no such bubble is under way.

In this paper we attempt to determine whether fundamentals' or contagion proxies explain stock price changes in the US market. Over the years, many other researchers have addressed these questions. Nevertheless, we expect to make a contribution in two main areas. First, we test for these effects while avoiding some of the criticisms to which these papers have been subjected. For example, we differentiate and test separately for bubbles and contagion effects, which are mixed in much of the literature. We propose the use of variables that permit a clear interpretation of the results. Specifically, both the dependent and independent variables are expressed as percentage changes. Also by using panel data we avoid changing the properties of the data. Lastly, we created models that can be used with actual market data, unlike many of those proposed in the literature. The second area where we expect to make a contribution is related to the econometrics used in this study since quantile regression with panel data has not been used in the financial literature as of today.

This paper is organized is as follows. In the following section we cover a review of the bubbles and contagion literature. In the third and fourth sections we present our hypotheses, and the data and methodologies used in our tests. In the two last sections we present our findings and conclusions.

I. LITERATURE REVIEW

Each major financial market crash has provoked studies trying to prove or disprove the existence of bubbles that could explain the crises. Time after time it has been hypothesized that asset prices can bubble and then crash to fundamentals' value. While prices are increasing investors may realize that the assets are overvalued when compared to their fundamentals. Nevertheless, speculators trade because they think they will get out in time or because the expected high return rewards them for the probability of a crash (McQueen and Thorley, 1994) (Russell, 1988) (Salant and Henderson, 1978).

Even though so much has been written about "bubbles," there is no exact definition of this word. In general, though, it is used to refer to asset prices that are not justified by the assets' fundamentals. When a bubble bursts, that is, when there is a great discontinuity in the market-clearing price, high price volatility results as a consequence of excess supply.

In reference to bubbles there are mainly two schools of thought within the academic community. Those who believe that bubbles do exist although due to methodology constraints it is difficult to prove their existence, and those who believe bubbles are an impossibility, even if over time their existence has not been ruled out. This divergence in opinion results from a disagreement about the definition of fundamentals, and the assumptions, power, and appropriateness of the models utilized to test for bubbles.

Those who believe financial asset prices sometimes deviate from their fundamental values have suggested several reasons to explain why bubbles are created and maintained. For example, it has been proposed that (1) irrespective of fundamentals self-fulfilling expectations can drive prices (Flood and Garber, 1994). Another idea is that (2) in as long as another investor is willing to purchase the same asset at a higher price fundamentals may be irrelevant to some speculators (Galbraith, 1955). Lastly, it has also been said that (3) short-term investment horizon decisions can be influenced by considerations unrelated to fundamentals, such as liquidity needs, accounting issues, etc. (Scharfstein and Stein, 1990).

Regardless of the arguments stated above, those within the financial community who do not believe bubbles can be formed explain each financial market crisis in terms of fundamentals. Their position is that: (1) there are strong theoretical arguments to support the belief that prices do not diverge from present value levels (Froot and Obstfeld, 1991). (2) There are multiple econometric difficulties in testing whether stock prices are more o less explosive than dividends (as a proxy for fundamentals) (Evans, 1991). (3) Prices can be justified by fundamentals not observed by the researcher (Hamilton and Whiteman, 1985).

In general, tests for bubbles fall under one of two categories. Within the first category one sets the null hypothesis that a bubble exists and attempts to reject it in favor of an unspecified alternative (Shiller, 1981) (Tirole, 1985) (Hamilton and Whiteman, 1985) (Kleidon, 1986) (Diba and Grossman 1987, 1988) (Allen and Gorton, 1988) (O'Connell and Zeldes, 1988) (Ikeda and Shibata, 1992) (Friedman and Aoki, 1992) (Charemza and Deadman, 1995) (Han, 1996).

The results of the tests performed by Kleidon (1986-7), Campbell and Shiller (1987), and Diba and Grossman (1988) using this method with prices and dividends do not seem to contradict the hypothesis that prices conform to market fundamentals. On the other hand, Han (1996) does not find there is cointegration between prices and fundamentals. Nevertheless, the ability of these tests to detect the existence of bubbles has been questioned. For example, Evans (1991) built a model with periodically collapsing bubbles not detectable by using standard tests to determine whether stock prices are more explosive or less stationary than dividends. Also, many of the critiques point out that these are joint tests of the no-bubble hypothesis. That is, the assumptions made about the model (the definition and relation between fundamentals – which are not observable- and prices), or the assumptions made about the time series properties of the fundamentals (Flood and Garber 1980) (Hamilton and Whiteman, 1985) (Bierman, 1995). In addition, failing to reject the presence of a bubble cannot be strictly interpreted as proving the bubbles' existence.

Within the second category one sets the null hypothesis that a model is correct and attempts to reject it in favor of another one that includes a bubble. This second category of tests examines returns for empirical attributes of bubbles such as autocorrelation, skewness, and kurtosis (see West, 1987) which result from the runs of positive abnormal returns and crashes (McQueen and Thorley, 1994) (Blanchard and Watson, 1982) Evans (1986). This method has been criticized on the basis that these attributes are also associated with fundamentals. In addition, the rejection of a structural model cannot be solely attributed to the presence of the bubble. It may simply be that the model is misspecified.

In response to the critiques against both categories of tests more sophisticated methodologies have been proposed in later studies. Also, a third group of researchers has tackled the subject in a completely different manner, such as proposing rules for identifying cyclical bubbles or creating theoretical models where bubbles can occur.

The bubble-related research has tried to answer the question of whether security prices are justified by the assets' fundamentals. The finding that, occasionally, prices of financial assets deviate from their fundamental values has been explained by speculative behavior that disappears after a certain period of time. Noise trader models, and psychological or behavioral models are being used to explain these changes in asset prices (Shiller, 1984) (Shiller and Pound, 1986) (West, 1988) (Galant, 1995).

Standard models of informed speculation assume traders have long-term horizons. Nevertheless, if traders have short-term horizons and there is no new information related to fundamentals, traders may follow the actions of other market participants (Orlean, 1989) (Lesourne, 1992). That is because of the suspicion that the other's behavior may be influenced by better information (Bikhachandani, Hirsleifer, and Welch, 1992).

The informational price theory (IPT) explains how prices reflect information about the expectations of future earnings. In the market, some agents purchase information relevant to their trading while others derive the information from the new price levels that result from the trade by 'informed agents'. Therefore, it is difficult to distinguish when actions result from information about "fundamentals" versus other agent's actions (Burness, Cummings, and Quirk, 1980).

DeLong, Shleifer, Summers, and Waldman (1990) demonstrate that shorter horizons on the part of "smart money" traders allow the behavior of noise traders to have a greater impact on asset prices. They argue that "if sophisticated investors' horizons are long, arbitrage becomes less risky and prices approach fundamental values" (p.713).

An inefficiency created by short horizon speculation is that traders may focus on poor quality data or on variables that have no relation to fundamentals. Speculators' demands depend on the information they observe. In forming their demands they take as given the number of speculators who are informed, the trading strategies of these speculators, and the pricing strategy of the market maker. In addition, liquidity traders have inelastic demands for the asset. Two main classes of models in which short trading horizons can lead to inefficiencies are noise trader models and behavioral models.

Noise trading models assume less than fully rational traders. The agents are called naïve traders, noise traders or chartists and make investment decisions based upon the study of past trends (Chiarella, 1992). DeLong et al. (1990) examine "positive feedback" traders who extrapolate past price trends and drive the asset price away from its fundamental values. In 1991, DeLong et al. develop a model with rational sophisticated traders and "noise traders." In this model, the proportion of noise traders increases when they are making higher returns than sophisticated traders. The assumption is that speculators think the bubble will last until they complete their trade.

Other papers investigate empirical clustering which result from momentum-following (positive feedback investment such as buying past winners or repeating the predominant buy or sell pattern from the previous period) and result in prices deviating from fundamentals (Lakonishok et al., 1991) (Grinblatt, Titman, and Wermers, 1995) (Falkenstein, 1996) (Wermers, 1999).

There have been several criticisms of the methodologies used in the noise trader models. For example, in the Bayesian Nash equilibrium approach the payoffs for investment strategies have to be specified at the bottom of the game tree. Also, the assumption is that when the informed traders succeed in manipulating the uninformed, they are able to realize the capital gains (sell the asset) without their sales affecting the uninformed trader's strategy. This two-agent, high-low demand framework is very simple and unrealistic. In addition, speculative bubbles arise in the Bayesian Nash equilibrium model due to the high-low quantity constraint. Without this constraint no there is no "one price target" that can announce high earnings. Therefore, uninformed traders may observe a price increase and wonder if it really reflects high earnings news.

Herd behavior is imitative behavior that results in contagion of opinion and actions. Managers may trade as a herd if they share an aversion to stocks with certain characteristics (Falkenstein, 1996) or they may ignore their private information because of the risk of acting differently from other managers (Scharfstein and Stein, 1990). Graham (1999) designs a model where the analysts with higher reputation herd to protect their status and salary. Graham (1999) develops a model in which an analyst is likely to herd if his private information is inconsistent with strong public information. His results indicate that a newsletter analyst is prone to herd on Value Line's recommendations. Also, it has been proposed that institutional investor trading patterns contribute to serial correlation in daily stock returns (Sias and Starks, 1997). In support of this proposition, Kelkisky (1977) found that stocks having the largest trade imbalances among investment companies (dollar purchases exceeding dollar sales) usually follow prolonged periods of positive abnormal stock returns. This is interpreted as evidence that some funds follow other leader funds in their purchases.

Under herd behavior, bubbles are explained as the consequence of infection among traders which results in clearing prices that deviate from fundamental values. The higher the returns the more willing the speculators will be to follow the crowd. This could partially explain excessive stock market volatility. The reason is that a group trading on the same direction will magnify price shocks (White, 1990). In this context, bubbles are thought of as a temporary phenomenon, which leads to price fluctuations around fundamental values.

Behavioral models try to "make known" or "disclose" the process of contagion. In many cases, this process is approached using probabilities to analyze the dynamics of systems (like the market) where the units (agents) that constitute the system (market) interact

(Hanken, 1983) (Weidlich and Haag, 1983). The interactions among this traders result in the mutual infection of attitudes and opinions (Kindleberger, 1989) (Topol, 1991) (Kirman, 1993) (Lux, 1995).

Over time, many researchers have used behavioral models of financial markets (Shiller, 1984) (Kindleberger, 1989) (Lux, 1995). Particularly, after Kindleberger (1989) explained the importance of psychological factors in historical financial crises, several authors have built a variety of models of stock market dynamics that explicitly include contagion of opinion and behavior. Thus, the findings of these models offer a behavioral explanation to the trading mechanism. Some examples are the papers by Lux (1995), Banerjee (1992) and Kirman's (1993) Devenow and Welch (1996).

Shiller and Pound (1986) surveyed institutional investors to determine the factors that went into their decision to buy a particular stock and found that the purchase of stocks that had had price increases was motivated by the opinion of others (other investment professionals, newsletters, etc.). Nevertheless, when selecting stocks with more stable prices, fundamentals' research was comparatively more important. These findings suggest it is possible that money managers could invest in stocks even if fundamentals advise differently. Within this paper, the authors also discuss classical epidemic models and make the point that direct "interpersonal communication among peers seems to produce the kind of attention and reassurance that leads to changes in behavior."

To test the existence of contagion one may look at variables such as volume, money flows, and volatility since noise trader models propose a causal relation between each of these variables and stock returns. That is because these relationships are consistent with two assumptions made in these models: the trading strategies pursued by noise traders cause stock prices to move, and noise traders use positive feedback trading strategies (DeLong, Shleifer, Summers, and Waldmann, 1990). Also, herd behavior can explain some of the incremental stock market variability because if many people follow the same trading rules price shocks will be magnified (Scharfstein and Stein, 1990).

In addition, many studies have tested for causality between stock price and volume (Gallant, Rossi, and Tauchen, 1994) (Campbell, Grossman, and Wang 1993) (Hiemstra and Jones, 1994). This line of research tries to clarify whether trading volume helps predict prices since volume represents information. Large positive price changes result in capital gains and provoke further transactions. Granger Causality Test and the Baek and Brock (1992) Test have been used to analyze this relationship. The evidence of the positive causal bi-directional relationship is not supportive of the efficient market hypothesis (Jennings, Starks, and Fellingham, 1981) (Silvapulle and Choi, 1999).

In this paper we will describe contagion as the trading pattern resulting from herding behavior. We also assume that bubbles are one of the consequences of such behavior. We will not further try to identify the events that could possibly trigger this herding behavior or the bursting of a bubble. It is sufficient to say that the contagion may be due to informational externalities or psychological factors.

Since our proxies for fundamentals are accounting variables it is also appropriate to briefly mention some of the accounting literature models and findings that relate to the relationship between accounting earnings and stock prices.

In general, the accounting literature has investigated the relationship between corporate revenues and financial asset prices in one of two ways. The first approach is to use event study methodology to investigate the impact of earnings announcements on stock prices. The second is to create different trading strategies to determine whether financial information is impounded in share prices.

Overall, it has been shown that the average explanatory power of single or multiple factor market models is minimal. That is, most researchers report small coefficients, and R^2s close to zero (Lev, 1989). Lev (1989), for example, suggests that the R^2s in earnings-returns regressions are "too low" to be economically important. This finding remains true even when one takes into consideration the effect of news on returns (Roll, 1988). In contrast, it has also been found that the explanatory power of these models for specific firms can be very large.

Several authors have proposed different reasons to explain the above findings. For example, Easton (1992) suggested that prices may respond to information that becomes public throughout the quarter. Equally, it would be possible that current events may not be reflected in the accounting earnings of the current period.

Another explanation provided by some of the researchers who looked into the subject of forecasting accuracy, is analyst over optimism. On average, the annual forecasting error (the difference between the expected and actual earnings growth), has been proposed to be around 7% (Frankel and Lee, 1996) (Harris, 1999).

In understanding the findings reported by different authors one should be aware that the results obtained from different studies may not be directly comparable. For example, one should not directly compare the R^2 of the models where level data was used (i.e. prices) with those models where returns were used (i.e. percentage changes in prices). These second ones will always be smaller because of scaling differences. Also, one cannot compare the results from models where data of different interval periods was used (i.e. quarterly earnings versus annual earnings, etc). The reason is that the longer the period the higher the R^2.

There is a general consensus that expected returns are notoriously difficult to predict for many reasons, including modeling and econometric problems. Therefore, reaching general conclusions about the predictability of returns of different models is not a straightforward endeavor, and, consequently, the literature provides ample evidence of conflicting findings. That remains the case whether we look at the bubble literature, the contagion literature, or the accounting literature as it relates to price predictability.

II. HYPOTHESES

We have already presented reasons why we feel it is worth investigating the hypothetical existence of bubbles within financial markets that are considered efficient. As previously stated, in terms of this paper, the only condition for bubbles to exist is that, at some point in time, the asset's market clearing price is not justified by its fundamentals. Here we propose that if prices reflect fundamentals, changes in fundamentals should be related to changes in prices.

Previous studies have claimed that new information about market fundamentals provides only a partial explanation of observed price fluctuations (Ohanian, 1996). It has been proposed that short-term fluctuations are caused by shifts in market psychology or events that have no direct bearing on business prospects or economic conditions. Some authors have suggested that bubbles are created and maintained because, irrespective of fundamentals, self-fulfilling expectations can drive prices (Food and Garber, 1994). Others have added that it is rational to purchase an asset when another investor is willing to purchase the same asset at a higher price (Galbraith, 1955).

In accordance with the idea that short-term variability in asset prices could be explained by causes other than fundamentals, we test the hypothesis of the existence of bubbles. Therefore, Hypothesis 1 proposes that there is not a significant contemporaneous relationship between changes in fundamentals and changes in stock prices. Thus, changes in the asset's fundamentals are not explanatory of changes in the asset's prices.

Hypothesis 1:

H_0: There is not a contemporaneous significant relationship between changes in fundamentals and changes in stock prices.

H_1: There is a contemporaneous significant relationship between changes in fundamentals and changes in stock prices.

In order to test Hypothesis 1 we need to explain the proxies for "fundamentals" used to test for bubbles in asset prices. Hamilton (1986) and Tirole (1985) among others proposed that the value of a financial asset is the present value of the future payoffs from the asset. Shiller (1981) suggested that one can use dividends or earnings to evaluate the present value of these future payoffs. Some researchers have observed that dividends are established only by some corporations, and after careful consideration of multiple issues including company maturity, expected future earnings, expected free cash flows, and smoothing. In the long run, whichever the dividend policy, it should bear relation to actual corporate earnings, since in time expected earnings are realized, and dividends can only be paid out of actual earnings. By extension, no matter how stock prices are determined, in the long run they should be related to the corporate actual earnings.

Market traders may not fully agree on what are the expected future cash flows of corporations, that is why some agents buy when other agents sale. But, if during a sustained period of time stock prices grow at a rate significantly different from the growth rate of the operating cash flows, the moment will come when the market clearing prices will no longer reflect the present value of discounted cash flows. Consequently, in order to ascertain whether there is a bubble, one can determine whether changes in share prices reflect changes in fundamental values. We can then justifiably compare prices' and earnings' growth rates to determine whether there is a significant relationship between these two variables.

In order to test Hypothesis 1 we use twelve models with different definitions of fundamentals. OLS, Panel Data, and Quantile Regression are used to test the hypothesis. In these models the firm's changes in stock prices are regressed on the proxies for fundamentals (see Data and Methodology for further explanation). These proxies include different earnings measures as well as the debt to equity ratio. The reason why the debt to equity ratio is included is to determine whether the market's reaction to quarterly accounting reports is due to a change in the capital structure of the corporations versus a change in accounting earnings.

An inefficiency created by short-horizon speculation is that traders may focus on poor-quality data or on variables unrelated to fundamentals. Therefore, if speculators have short-term horizons, they may herd on the same information instead of trading on the underlying fundamentals. The resulting market-clearing prices could then deviate from those justified by the assets' fundamentals.

Since much of the literature points to contagion of opinion that results in herding behavior among agents as one of the hypothetical causes for the creation of bubbles, we examine the contemporaneous relationship between changes in prices and changes in proxies for herding behavior. The idea is to determine whether changes in herding behavior proxies are explanatory of price changes.

<u>Hypothesis 2:</u>

H_0: There is a contemporaneous significant relationship between changes in herding behavior proxies and changes in asset prices.

H_1: There is not a contemporaneous significant relationship between changes in herding behavior proxies and changes in asset prices.

To test the existence of herding behavior that results in contagion we look at three proxies for herding behavior: volume, money flow, and volatility. That is because noise trader models propose a causal relation between each of these variables and stock returns. The reason is that these relationships are consistent with two assumptions made in these models: the trading strategies pursued by noise traders cause stock prices to move, and noise traders use positive feedback trading strategies (DeLong, Shleifer, Summers, and Waldmann, 1990). For example, herd behavior can explain some of the excessive stock market volatility because a large group trading on the same direction will tend to magnify price shocks (White, 1990). In addition, many studies have also tested for causality between stock price and volume (Gallant, Rossi, and Tauchen, 1994) (Campbell, Grossman, and Wang 1993) (Hiemstra and Jones, 1994). The idea is that large positive price changes result in capital gains. Of course, the higher the returns the more willing the speculators will be to follow the crowd (Scharfstein and Stein, 1990) which will provoke further transactions. Lastly, it has been proposed that institutional investor trading patterns contribute to serial correlation in daily stock returns (Sias and Starks, 1997). In support of this proposition, Kelkisky (1977) found that stocks having the largest trade imbalances among investment companies (dollar purchases exceeding dollar sales) usually follow prolonged periods of positive abnormal stock returns. This is interpreted as evidence that some funds follow other leader funds in their purchases. Because of this observed imitative conduct, it has been said that capital gains are most likely determined by the behavior of other agents (Grossman and Stiglitz, 1976).

In these models the firm's changes in stock prices are regressed on the proxies for herding behavior (see Data and Methodology for further explanation). OLS, Panel Data, and Quantile Regression are used to test the hypothesis.

III. DATA AND METHODOLOGY

In order to run the models needed to test our hypotheses, two kinds of data are collected. The data needed to test Hypothesis 1 (relationship between stock prices and fundamentals) are summarized and described in Tables 1 and 2. The data used to test Hypothesis 2 (relationship between prices and contagion proxies) are described in Tables 3 and 4.

The initial sample used to test these hypotheses consists of all the companies included in the S&P500 Index. These companies should be the most accurately priced since the information relevant to their operations is widely available. The final sample for each model varies with the availability of the accounting quarterly data needed for the construction of the independent variables. All the data are obtained from the Compustat tapes.

We work with panel data (cross section and time series) versus creating indices and weighted averages. Even though using panel data presents some econometric challenges, it enlarges the sample size allowing us to obtain more information and increase the significance of our findings. In addition, manipulating the data to create indices and weighted averages could obscure the interpretation of our results. 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. Since quarterly earnings are publicly announced and the market adjusts expectations accordingly, quarterly data is deemed appropriate. The benefits from using quarterly data are assumed to outweigh the fact that it might not always be as accurate as the yearly data because of later adjustments by the corporations. Annual data 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 Hypothesis 1 we construct twelve different models. The dependent variable is always percentage changes in quarterly stock prices. The independent variables representing the fundamentals or the number of independent variables are different for each model. The reason is to consider other variables other than revenues. For example, if changes in operating costs are higher than changes in operating revenues the net effect is negative. Therefore, following revenues alone as a measure of growth is not appropriate. In addition, other 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. For example, investment in research and development (R&D) which may be a proxy for future growth in the technology and pharmaceutical industries and consequently a positive signal for the market, results in a reduction of earnings before interest and taxes (EBIT). That is why our fundamentals' proxy variable is different in each model.

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 tests include the same companies or number of companies, we work with unbalanced panel data. 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 percentage changes in quarterly EBIT. In subsequent models depreciation, R&D, investment in net working capital, and capital investment are added back to EBIT. Five of these models also include the debt-to-equity ratio to capture the effect on the stock price of any changes in the capital structure of the corporation.

One problem is that as additional data is needed to construct the described independent variables, the sample size is reduced. Therefore, another reason to construct different proxies is to enlarge the sample size. A complete description of all the data used to build each model to test Hypothesis 1 is presented in Table 1 and a description of the variables is provided in Table 2.

The data related to Hypothesis 2, which proposes a contemporaneous relationship between percentage changes in prices and percentage changes in herding behavior proxies, is presented and described in Tables 3 and 4. All the data included in these tables is monthly and was obtained from the Compustat tapes.

In reference to Table 3, the original sample includes all the corporations listed in the S&P 500 Index. One more, the main criteria for the selection of the companies listed in the S&P500 is that they represent a large percentage of the stock exchange market. This fact should increase our ability to generalize the results.

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. This is not a problem because we are working with unbalanced panel data.

TABLE 1
(Models to test Hypothesis 1)

Model #	Period # Observations # Companies	Dependent variable $\Delta P = \frac{P_t - P_{t-1}}{P_{t-1}}$	Independent variables $\Delta R = \frac{R_t - R_{t-1}}{R_{t-1}}$	$\Delta DE = \frac{DE_t - DE_{t-1}}{DE_{t-1}}$
1	1988-1998 9162 230	P= price		$\mathrm{DE} = \frac{D_{it}}{E_{it}}$
2	1988-1998 9162 230	P= price	R= $\mathrm{EBIT_{it}}$	$\mathrm{DE} = \frac{D_{it}}{E_{it}}$
3	1988-1998 6856 172	P= price	R= $\mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}}$	
4	1988-1998 6395 161	P= price	R= $\mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}}$	$\mathrm{DE} = \frac{D_{it}}{E_{it}}$
5	1989-1998 4140 115	P= price	$\mathrm{R} = \mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}} + \mathrm{NWC_{it}} + \mathrm{Capital\ investment_{it}}$	
6	1993-1998 855 45	P= price	$\mathrm{R} = \mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}} + \mathrm{NWC_{it}} + R\&D_{\mathrm{it}} + \mathrm{Capital\ investment_{it}}$	
7	1993-1998 831 44	P= price	$\mathrm{R} = \mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}} + \mathrm{NWC_{it}} + R\&D_{\mathrm{it}} + \mathrm{Capital\ investment_{it}}$	$\mathrm{DE} = \frac{D_{it}}{E_{it}}$
8	1988-1998 9916 249	P= price	R= $\mathrm{EBIT_{it}}$	
9	1988-1998 5985 150	P= price	$\mathrm{R} = \mathrm{EBIT_{it}} + \mathrm{Depreciation_{it}} + \mathrm{NWC_{it}}$	
10	1988-1998 8609 216	P= price	$\mathrm{R} = \mathrm{EBIT_{it}} + \mathrm{NWC_{it}}$	
11	1989-1998 10221 284	P= price	R= FCF_{it}	$\mathrm{DE} = \frac{D_{it}}{E_{it}}$
12	1989-1998 10978 305	P= price	R= FCF_{it}	

TABLE 2
(Description of variables in models to test Hypothesis 1)

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

We create three additional models using monthly data to determine the predictability power of the herding behavior proxies. Again, the dependent variable is always percentage changes in prices while the independent variables reflect percentage changes in money flow, volume and volatility.

TABLE 3
(Models to test Hypothesis 2)

Model #	# Years # Observations # Companies	Dependent variable: $\Delta DV = \frac{DV_t - DV_{t-1}}{DV_{t-1}}$	Independent variables $\Delta IV = \frac{IV_t - IV_{t-1}}{IV_{t-1}}$
Model 1	1988-1998 55077 441	DV= Price close	IV = Money Flow
Model 2	1988-1998 55077 441	DV= Price close	IV = Range
Model 3	1988-1998 55077 441	DV= Price close	IV = Common Shares Traded

TABLE 4
(Description of variables in models to test Hypothesis 2)

Variable	Description (all monthly data)
Price close	Absolute close market price per corporation and calendar month.
Price high	Absolute high market price per corporation and calendar month.
Price low	Absolute low market price per corporation and calendar month.
Common shares traded	Monthly number of shares traded per company and month. The shares of corporations that trade in more than one exchange are added together.
Mean	Absolute monthly high price plus absolute low monthly price divided by two.
Range	Absolute monthly high price minus absolute monthly low price.
Percentage return	Calculated as specified in Table 3 using Price Close.
Money flow	Mean multiplied by Common Shares Traded.

METHODOLOGY

Our goal is to explore potential short-run predictability of asset prices. For this purpose we use traditional conditional mean models such as OLS and panel data analysis, as well as the semiparametric method of quantile regression. OLS is used as a benchmark model since it assumes that prices across companies and time are identically and independently distributed, a clearly unreasonable assumption in this scenario. To fix this potential problem, panel data analysis (Fixed, Between and Random Effects models) takes into account potential heterogeneity across time and companies. In addition we also apply quantile regression on the Between data, i.e., on the company averages across time. Quantile regression is used to obtain a better idea of the effects of regressors on asset prices. This is because it provides a complete picture of the distribution of prices conditional on the explanatory variables. Therefore, it allows us to assess the impact of these variables on different parts of the return distribution. Specifically, in this study, we could expect to find that fundamental variables (like debt to equity ratio and earnings) have a statistically significant positive coefficient on all quantiles but the highest. The interpretation is that fundamental variables have explanatory power for most changes in prices other than those we hypothesize to be related to the bubble. On the other hand, we can expect the proxies for herding behavior (like volume) to be significant in explaining only away from the median quantiles. If these asymmetric effects are found, they could be interpreted as evidence that when a bubble has formed, fundamentals are not relevant but non-fundamentals are, while fundamentals are important when no such bubble is under way.

This section is broken into four subsections. Subsection 1) discusses OLS estimation of the model and the statistical assumptions necessary its consistency. This is the simplest independently and identically distributed (iid) error case and it is very restrictive. To deal with the problems arising from this restrictiveness subsection 2) introduces less restrictive assumptions and discusses between, within, and random effects estimation. To deal with possible endogeneity (orthogonality) problems subsection 3) introduces Hausman and Taylor (1981) instrumental variables estimation for panel data. Subsection 4) discusses quantile regression.

The purpose of this estimation is to determine whether there is a short-term linear relationship between returns in stock prices and returns in earnings and changes in capital structure. That is, if earnings and capital structure can be predictors for stock prices.

Our model is given by

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

where

$$\Delta P_{it} = \frac{P_{it} - P_{i(t-1)}}{P_{i(t-1)}}$$

and P_{it} is quarterly closing stock prices for firm *i* at time *t*. To simplify notation, we are going to use $y = \Delta P$.

X_{it} denotes a set of independent variables, which are the proposed predictors of changes in stock prices. In particular, X_{it} denotes, ΔDE and ΔR, as the case may be. The debt/equity ratio *(DE)* is used as a proxy for capital structure, constructed as follows

$$\Delta DE_{it} = \frac{DE_{it} - DE_{i(t-1)}}{DE_{i(t-1)}}$$

Where *DE* denotes quarterly debt/equity ratio for firm *i* at period *t*

The second independent variable ΔR is the specific proxy for earnings specified in Table 1. The changes are calculated in the following manner:

$$\Delta R = \frac{R_t - R_{t-1}}{R_{t-1}}$$

1) <u>OLS Estimation</u>

We first consider the simplest possible estimation method, to perform OLS on the pooled data.

Let $\tilde{y}_i$ be the vector of observed price changes for firm i, i.e., $\tilde{y}_i = (y_{i1}, y_{i2}, \ldots, y_{iTi})'$. Then we stack the data as follows:

$$y = [\tilde{y}_i'_1, \tilde{y}_i'_2, \ldots, \tilde{y}_i'_N]'.$$

Let $\tilde{X}_{Ki}$ be the vector of observed values of the X_K variable for the firm i, i.e.,

$$\tilde{X}_{Ki} = (X_{Ki1}, X_{Ki2}, \ldots, X_{KiTi})'.$$

Then we stack the data as follows:

$$X_K = [\tilde{X}'_{Ki1}, \tilde{X}'_{Ki2}, \ldots, \tilde{X}'_{KiN}]'.$$

Finally,

$$X = \{X_K\}^K_{k=1} = \{X_1|X_2|\ldots|X_K\}$$

$$Y = X\beta + \varepsilon.$$

$$\hat{\beta}_{OLS} = (X'X)^{-1} X'Y.$$

Under the assumption that the error terms, ε_{it}, are iid across i and t, pooled OLS estimation provides consistent and efficient estimates of the parameters in (1). Nevertheless, it is worth n oting that the iid assumption is very restrictive and will be relaxed in later sections.

2) Random and Fixed Effects Estimation

The assumption that ε_{it} is ~ iid $(0,\sigma^2)$ for all i and t is very restrictive. Possible violations of this assumption include serial correlation within individuals and heteroskedasticity across individuals in the sample. To accommodate possible violations of the iid assumption we consider random and fixed effects estimation in turn.

a) Random Effects

In the random effects model the error term ε in (1) has the following structure

$$\varepsilon_{it} = \alpha_i + \eta_{it} \qquad (i = 1,\dots,N;\ t = 1,\dots,T) \qquad (2)$$

where α_i is an individual specific shock and η_{it} is uncorrelated with X_{it}.

In particular we assume

$$E(\eta \mid X) = 0 \qquad E(\eta\eta' \mid X) = \sigma^2_\eta I_{NT}$$

$$E(\alpha_i\, \alpha_j \mid X) = 0, \text{ for } i \neq j \qquad E(\alpha_i\, \alpha_i \mid X) = \sigma^2_\alpha \qquad (3)$$

$$E(\alpha_i\, \eta_{jt} \mid X) = 0 \qquad E(\alpha_i \mid X) = 0$$

Given this assumption, the error covariance of t he disturbance term of each individual cross section unit is given by

$$\Sigma = E[\varepsilon_i \varepsilon_i'] = \sigma^2_\eta I_T + \sigma^2_\alpha ii' \qquad (4)$$

Then the covariance matrix for the error term for all the observations can be written as

$$\Omega = I_N \otimes \Sigma \tag{5}$$

Given an estimate for Ω, Feasible Generalized Least Squares (FGLS) will provide consistent and asymptotically efficient estimators for the parameters in model (1). To obtain such an estimate note that straight-forward calculations show that

$$\Sigma^{-1/2} = (1 / \sigma_\eta) [I_T - (((1- \theta) /T) ii')] \tag{6}$$

where $\theta = \sqrt{[\sigma^2_\eta / (T\sigma^2_\alpha + \sigma^2_\eta)]}$

Simple analysis of variance arguments can provide consistent estimators for σ^2_η and σ^2_α in θ. Alternatively, one may write the random effects estimators as a weighted average of the between and the within estimators, given by

$$\hat{\beta}_{GLS} = \Delta\hat{\beta}_B + (I - \Delta)\hat{\beta}_W$$

where

$\Delta = (\Sigma_B + \Sigma_W)^{-1}\Sigma_W$ and Σ's are the variance-covariance matrices. This is frequently

known as the Nerlove-Balestra estimator (see Maddala, 1971).

b) Between and Within Estimation

In this subsection we consider two consistent estimators for panel data models. The first one is obtained by converting all the data into individual specific averages and perform OLS on this derived data set. More specifically, we perform OLS on

$$\bar{P}_{i\cdot} = \bar{X}_{i\cdot}\, \beta + error$$

$$where\ \bar{P}_{i\cdot}\ is \tag{7}$$

$$\bar{P}_{i\cdot} = 1/T \sum_{t=1}^{T} y_{it}$$

In matrix notation, let D be a $NT \times N$ matrix of N dummy variables corresponding to each cross-section unit, and let $P_D = D(D'D)^{-1} D'$ be the projection matrix that transforms the data into individual specific means, given by

$$P_D = I_N \otimes 1/T\, i_T i_T' \tag{8}$$

The *between estimator* is then defined as

$$\hat{\beta}_B = (X'P_DX)^{-1} X'P_Dy \quad (9)$$

The second of these estimators utilizes the information thrown away by the between estimator. Let $M_D = I_{NT} - P_D$ be the matrix of deviations from individual specific means. The *within estimator* is defined as

$$\hat{\beta}_W = (X'M_DX)^{-1} X'M_Dy \quad (10)$$

The residuals from the between and within models can be used to provide estimates for the variance of η and α. In particular consistent estimates are obtained by

$$\hat{\sigma}^2_\eta = [1 / (NT - Nk - N)] \; \hat{u}'_W{}' \hat{u}_W$$

$$\hat{\sigma}^2_B = (\hat{u}'_B \hat{u}_B) / (N\text{-}k) \quad (11)$$

$$\hat{\sigma}^2_\alpha = \hat{\sigma}^2_B - \hat{\sigma}^2_\eta / T$$

where $\hat{u}_W$ are the residuals from the within regression and $\hat{u}_B$ are the residuals from the between regression. These can be used to construct $\hat{\theta}$ which in turn provides an estimate for Σ. Given $\hat{\Sigma}$, we also have an estimate of $\hat{\Omega}$ which can be used to estimate the random effects model discussed in the previous subsection by FGLS.

3) Quantile Regression

A major problem with regression in general, is that it provides a very general description of the relationship between variables. The prevalent way of estimating the relationship among a dependent variable Y and a set of independent variables X, is by formulating a model for the mean of Y conditional on X such as

$$Y = X\beta + u \quad (12)$$

where u is a vector of independent error terms whose i-th component has an unspecified distribution. In the case of iid errors we can obtain a complete description of (1) by the Least Squares estimates of the conditional mean function and a measure of dispersion. Nevertheless, since in the case of our data the iid linear model may not provide a complete characterization of the conditional distribution of Y on X, some measures, other than the mean, are called for.

The quantile regression model by Koenker and Bassett (1978) provides a semiparametric alternative to least squares that handles heterogeneously distributed unobservables in an informative manner. The quantile regression estimator is robust to outlying observations in Y and it allows one to examine the case when the estimated $\beta(\tau)$ coefficients differ systematically across the τ's. A possible explanation for this condition is that the marginal effect of a particular explanatory variable is not homogeneous across different quantiles of the conditional distribution of *Y*. For example, the model for the τ-th conditional quantile of *Y*:

$$Quant_{\tau}\,[Y/X] = X\beta(\tau) \qquad (13)$$

The orthogonality condition on u is assumed for $Quant_{\tau}\,(u/X)$, the τ-th conditional quantile of the error term is assumed to be constant, meaning that it does not depend on *X*. In this way, a set of quantile regression curves is created for each τ. This set of regression curves provides a more detailed characterization of the relationship between *Y* and *X* than that given by the mean regression (see attached graph for a comparison of OLS and quantile characterization of homoskedastic and heteroskedastic models).

The estimation of the $\beta(\tau)$ (regression quantiles) is based on n observations of *Y*, and *p* explanatory variables from the matrix *X*. The estimates of $\beta(\tau)$ are obtained from

$$\min_{\beta \in R^{K}} N^{-1}\, \Sigma\, \rho_{\tau}\,(y_i - X_i\beta) \qquad (14)$$

where $\rho_{\tau}(\nu) \equiv [\tau - 1(\nu < 0)]\ \nu$, the *check function* of Koenker and Bassett (1978).

To accommodate the panel structure of our data, we are going to apply quantile regression on the between data i.e. on the individual specific averages. Our model is given by

$$Quant_{\tau}\,[P_{i}.\ |\ X_{i}\bullet\ ] = X_{i}\bullet\,\beta_{\tau} \qquad (15)$$

the estimator for β_{τ} is consistent and asymptotically normal. Standard errors for the estimators can be obtained by either asymptotic theory or bootstrap methods.
The Pseudo-R^2 of quantile regression constitutes a local measure of goodness-of-fit for a particular quantile rather than a global measure of goodness-of-fit over the whole conditional distribution, like R^2. The Pseudo R^2 or $R^2(\tau)$ is given by [1 – ($\sum$ of the weighted deviations about the estimated quantile/ $\sum$ of the weighted deviations about raw quantiles)].

RESULTS

In Table 5 we present a summary of the results of the twelve models and three methodologies used to test Hypothesis 1. The columns are self-explanatory. N/A means no applicable, NS means not significant, S means significant and the subscript indicates whether significance was found in the coefficient of the between, within or GLS estimator.

The OLS estimator shows that in models 2 and 8, the coefficients of the independent variable ΔR are significant at conventional levels. In both cases, ΔR represent Δ in EBIT. The difference between these two models is that the first one includes a second independent variable. In addition, in model 11 the independent variable ΔDE is significant at the 10% level. The R^2 (the proportion of the total variation in ΔP, explained by the linear combination of the regressors) in models 2 and 8, is 0.0004. Also, the magnitude of the coefficients, 0.0001693 and 0.0001924, is close to zero. In the case of model 11, the R^2 is 0.0003 and the coefficient is -.0003158.

Given the above observations, we have to conclude that even in the cases where changes in revenues are significant, they have minimal explanatory value for changes in stock prices. It is apparent that for the most part our independent variables do not explain the variation in the dependent variable.

TABLE 5
SUMMARY OF SIGNIFICANT RESULTS BY TEST AND VARIABLE
(Hypothesis 1)

Model #	Revenues			Debt/Equity		
	POOLED	PANEL	QUANTILE	POOLED	PANEL	QUANTILE
1	N/A	N/A	N/A	NS	NS	NS
2	.0001693 P>|t|= .071 R^2=.0004	.0001944 S_W .0001727 S_{GLS} P>|t|= .041/.065 R^2=.0004/.0005	NS	NS	NS	NS
3	NS	.0006899 S_B P>|t|= .088 R^2=.0171	NS	N/A	N/A	N/A
4	NS	.000685 S_B P>|t|= .092 R^2=.0181	NS	NS	NS	NS
5	NS	NS	NS	N/A	N/A	N/A
6	NS	NS	NS	N/A	N/A	N/A
7	NS	NS	NS	NS	NS	NS
8	.0001924 P>|t|= .04 R^2=.0004	.0002183 S_W .0001955 S_{GLS} P>|t|= .022/.037 R^2=.0005/.0004	NS	N/A	N/A	N/A
9	NS	NS	NS	N/A	N/A	N/A
10	NS	NS	NS	N/A	N/A	N/A
11	NS	NS	NS	-.0003158 P>|t|= .073 R^2=.0003	-.0003118S_W -.0003156S_{GLS} P>|t|= 081/.073 R^2=.0003/.0003	NS
12	NS	NS	NS	N/A	N/A	N/A

We have already mentioned that OLS ignores the panel structure of the data by assuming that the ε_{it} are iid and, therefore, these findings may turn out to be the result of this unreasonable assumption. The results of the panel data analysis take into account the panel structure of the data. Under these assumptions, the results show that in four out of twelve, models 2, 3, 4, and 8, the coefficients of ΔR are significant at conventional levels. In the case of models 2 and 8, ΔR represent Δ in EBIT; and in the case of models 3 and 4, ΔR are Δ in the sum of EBIT + Depreciation. Even though, with respect to the revenue proxy, by recognizing the panel structure of the data we have found two additional significant coefficients, the R-squares remain close to zero. Still it seems that our independent variables do not explain much of the variation in the dependent variable.

In reference to ΔDE, none of the coefficients have been found significant except for the within and random effects estimators in Model 11. In this case, the variable is significant at the 10% level, the overall R-squared is 0.0003, and the coefficients are -.0003118 and -.0003156.

In general, these findings are interesting for what they fail to convey: that to a large extent returns are related to positive changes in earnings, and that the addition of debt into the capital structure of corporations adds value to these businesses.

Finally, the last column presents the results of the quantile regression. Even though most of the results presented so far do not exhibit mayor significant findings, we can still investigate the relationship between fundamentals and prices to explore whether changes in earnings affect changes in prices in an asymmetric manner by using quantile regression. None of the quantiles of any of the 12 models are found significant for either variable, therefore, we strongly suspect that prior findings obtained with the OLS estimator and panel data analysis are spurious, and mainly the result of the methodologies' assumptions.

Given the findings obtained from the quantile regression, we therefore accept our Hypothesis 1 and conclude that there is not a statistically significant relationship between changes in security prices and changes in the fundamentals as defined in this paper.

In interpreting our results, we have to keep in perspective that what we are analyzing is the relationship between percentage changes in quarterly accounting data and percentage changes in quarterly stock prices. We are not trying to find all the explanatory variables of a model of price changes per se.

Even though in the pooled estimator and panel data analysis R^2 are close to zero, these findings are consistent with prior research (Brown et al., 1999). Lev (1989) for example, argues that the R^2 in earnings-returns regressions is "too low" to be economically relevant. Brown el al. (1999) proposes that the differences between the too low R^2 in returns regressions and the higher R^2 in levels regression are caused by scale effects. This idea has to be considered when one is tempted to make comparisons across models.

Other researchers have proposed that the average explanatory power of market models is quite modest (whether it is a single or multiple factor model), even if for some specific firms it is extremely large. Also, those who have taken into account the effect of news on returns point out that this does not seem to materially increase the R^2s (Roll, 1988).

Another explanation for the low explanatory value of the independent variables using the two first methodologies, is that it is always possible that prices respond to information related to fundamentals that is leaked throughout the quarter. Easton (1992) proposed that earnings would not be a perfect summary of events of the corresponding return interval. That is because (1) value-relevant events observed by the market (and captured in returns) in the prior period may affect accounting earnings in the current period and (2) value relevant events observed by the market in the current period may not be reported in accounting earnings of the current period.

Yet, some other authors have looked into forecasting accuracy of analysts in the short-run horizon (Frankel and Lee, 1996) (Harris, 1999). In general, they report analyst over optimism of expectations, particularly associated with high forecast earnings growth, low book-to-price ratio, and high past sales growth. Most of their forecasting error found is random, but over half of it arises from the deviations of individual firm growth from average industry growth. The main idea is that the accuracy of the forecasting varies substantially with the characteristics of the company being forecasted.

We are aware that low R^2s have been previously reported in the literature. Nevertheless, the fact that our findings are not consistent across OLS and panel data analysis, and that no significance was found using quantile regression and non-parametric methods to calculate standard errors, make us strongly suspect that the results of the first two methodologies are spurious. The reported findings could be mainly the result of the assumptions of the methodologies themselves.

Because of our data, and the methodology we followed our findings are not directly comparable with those obtained using dividends as a proxy for earnings, those event studies reporting market reaction to dividend announcements, papers analyzing levels, or any studies using indices instead of panel data.

Another consideration is that the R^2 cannot be compared directly with those studies that have used annual or longer interval period data. That is because it has been shown that as the return interval increases, the explanatory power of earnings increases too. For example Easton et al (1992) provided evidence that indicated the R^2 raises from about 5% for a one-year return interval to 33% for a five-year interval. In addition, other studies have demonstrated that higher earnings sensitivity coefficients can be obtained from levels of prices and earnings rather than from first difference formulations (Kothari and Zimmerman, 1995).

Even though it seems that coefficients obtained from levels are higher, it has been argued that levels do not reflect an informational perspective. We agree with Easton (1998) in that the explanatory power of levels regressions can b e misleading, and that is questionable what inferences one can draw from these regressions without controlling for the size effect. These are some of the arguments we use to propose the use of percentage changes instead.

In this n ext section we are going to test ou r Hypothesis 2 and examine whether our models pick up on this contagion of opinion effect. In order to test for this hypothesis we use three additional independent variables proxies for herd behavior. The first one is percentage changes in monthly money flow (MF). This variable captures the additional capital invested each month to purchase each companies' stock. The second is percentage changes in the monthly price range (RANGE). This variable is a measure of changes in volatility. The third variable is pe rcentage changes in the number of shares traded (VOLUME). The data set includes 441 companies from the S&P500 that provide the necessary monthly information for the period 1988-1998. A complete description of the variables and models used in this section is provided in Tables 3 and 4.

TABLE 6
SUMMARY OF SIGNIFICANT RESULTS Δ MF
(Hypothesis 2)

POOLED			PANEL			QUANTILE			
Coef.	P>|t|	R^2	Coef.	P>|t|	R^2	Quantile	Coef.	P>|t|	R^2
						.35	.0176884	.032	.0070
.0161103	.000	.0182	$.0347032_B$	.000	.0779	.40	.0184599	.032	.0127
			$.0159614_W$	.000	.0179	.45	.0193531	.039	.0188
			$.0161083_{GLS}$	.000	.0182	.50	.0275592	.011	.0235
						.55	.0326997	.008	.0273
						. 60	.03852	.005	.0345
						.65	.0489202	.003	.0449
						.70	.0656631	.000	.0615
						.75	.067052	.000	.0770
						.80	.0683866	.000	.0957
						.85	.0881746	.000	.1191
						.90	.0985151	.000	.1350
						.95	.1608707	.000	.1675

In reference to Model 1 (m oney flows), the results indicate that the coefficients of changes in money flow are p ositive and significant at the 1 % level for q uantiles 35%-95%. Since the size of the coefficients and Pseudo-R^2 increase with the quantiles, we conclude that money flows seem to be important in ex plaining positive price changes and the greater the price change the greater the significance of this variable. Therefore, money flows is a significant for winners or companies with, on average, positive price changes, but not for losers or companies with, on average, negative price changes.

TABLE 7
SUMMARY OF SIGNIFICANT RESULTS ΔRange
(Hypothesis 2)

POOLED			PANEL			QUANTILE			
Coef.	P>|t|	R^2	Coef.	P>|t|	R^2	Quantile	Coef.	P>|t|	R^2
						.10	.0420711	.024	.0220
.0177714	.000	0174	0889881_B	.000	.1357	.15	.0552295	.001	.0321
			$.0175803_W$	.000	.0172	.20	.0509389	.000	.0405
			$.0177714_{GLS}$	.000	.0017	.25	.0526525	.000	.0424
						.30	.0568859	.000	.0425
						.35	.0632057	.000	.0450
						.40	.0649983	.000	.0503
						.45	.0647331	.000	.0545
						.50	.076603	.000	.0592
						.55	.0761761	.000	.0612
						. 60	.0868224	.000	.0649
						.65	.089694	.000	.0711
						.70	.0905482	.000	.0778
						.75	.1071273	.000	.0796
						.80	.117309	.000	.0883
						.85	.1132171	.000	.1002
						.90	.140075	.000	.1119
						.95	.2584584	.000	.1288

In the case of Model 2 (ΔRange), the findings show that our proxy for volatility is significant for quantiles 10% and up. Just as in the case of money flows, the size of the coefficients and Pseudo-R^2 increase with the quantiles. The meaning is that changes in the range are important in explaining all price changes and the greater the change the more significant is this variable.

TABLE 8
SUMMARY OF SIGNIFICANT RESULTS Δ Volume
(Hypothesis 2)

POOLED			PANEL			QUANTILE			
Coef.	P>|t|	R^2	Coef.	P>|t|	R^2	Quantile	Coef.	P>|t|	R^2
.0053365	.000	.0019	$.0173757_B$ $.0052463_W$ $.0053312_{GLS}$	.006 .000 .000	.0171 .0018 .0019	.75 .80 .85 .90	.0333786 .0464091 .0545433 .0593327		

In Model 3 (Δ Volume), the results show that changes in the volume of shares traded is positive and significant for quantiles 75%-90%. Also, the coefficient of the independent variable and the Pseudo-R^2 increase with greater quantiles. The meaning is that changes in the number of shares traded is important in explaining the largest positive price changes (remember that the 75% quantile means that 75% of the dependent's variable distribution is below).

In the three cases, the constant is always significant increases steadily with the quantile. This indicates that there is a tendency for prices to increase even after we take into consideration the effect of the independent variables. Given these significant findings, we do not reject Hypothesis 2.

Our results in this section are consistent with those of other authors in the literature who identified the positive relationship between returns and volume, money flow, and volatility. Noise trader models propose a causal relationship between each of these variables and returns. That is because these relationships are consistent with two assumptions made by these models: trading strategies pursued by noise traders cause stock prices to move, and noise traders use positive feedback trading strategies. Also, herd behavior explains some of the excessive stock market volatility because a large group trading in the same direction will magnify price shocks (Beaver, 1968) (Clark, 1973) (Epps and Epps, 1976) (Smirlock and Starks, 1988) (DeLong, Shleifer, Summers, and Waldmann, 1990) (Scharfstein and Stein, 1990) (Gallant, Rossi, and Tauchen, 1994).

Our finding about the incremental explanatory value of the variables for greater positive price changes (higher quantiles and Pseudo-R^2) is consistent with two theories. First, the idea that noise traders follow feedback rules and buy when others buy (DeLong et al., 1991) (Chiarella, 1992). Second, with the informational price theory, which explains how some agents derive information from the new price levels that result from the trade by agents who purchase information. In light of volume or price information, agents will disregard their own private information and follow the behavior of the majority (Graham, 1999).

Beaver (1968) also proposes an explanation for the positive relationship between volume and variability. His idea is that because willingness to pay is greatest for optimistic investors and because trading activity arises from an increase in the divergence of opinion among investors, greater trading tends to occur with price increases. It has also been argued that trading is repressed for bad news information events because the cost of short-selling common shares is greater than purchasing.

Taken together, the findings seem to support the suggestions by different authors (i.e. Shiller and Pound, 1986) that changes in financial asset prices can be better explained by behavioral factors resulting from contagion of opinion, than by earnings information.

CONCLUSION

The primary purpose of this paper has been to investigate the existence of in the US stock market. We have proposed that if financial asset prices reflect fundamentals, changes in the corporation's fundamentals should be explanatory of changes in the same companies' share prices. To test this general hypothesis, a number of testable implications are derived and tested.

Previous studies have claimed that new information about market fundamentals provides only a partial explanation of observed price fluctuations (Ohanian, 1996). It has been suggested that while long-term movements in securities' prices correspond to changes in fundamentals, short-term fluctuations can be caused by shifts in market psychology or events with no direct bearing on business prospects or economic conditions. Those who believe that financial asset prices sometimes deviate from their fundamental values have listed a variety of reasons why bubbles are created and maintained. Different authors have proposed that self-fulfilling expectations alone can drive prices (Food and Garber, 1994), or that there may be other short-term needs, such as insufficient liquidity, accounting issues, and managerial considerations (Scharfstein and Stein, 1990) (Froot, Scharfstein, and Stein, 1992) (Wermers, 1999).

We acknowledge the possibilities stated in the above paragraph; therefore, the objectives of this paper are to test whether contagion proxies are explanatory of price changes (Hypothesis 2) as well as to test for the existence of bubbles in the short-run (Hypothesis 1) scenario.

Hypotheses 1 and 2, regard the existence of statistically significant contemporaneous relationships between changes in asset prices and an array of alternative measures of company fundamentals and contagion proxies. Specifically, Hypothesis 1 proposes the lack of a contemporaneous significant relationship between changes in fundamentals and changes in stock prices, while Hypothesis 2 suggests contagion proxies are explanatory of price changes.

To test our hypotheses related to the contemporaneous we use Ordinary Least Squares estimation, as well as, Conditional Expectation and Quantile Regression models for panel data.

Contrary to previous studies that use either cross-section data of many companies on a fixed point of time, or time series data of some market index, we utilize panel data. This has the advantage of taking into account variation across both companies and time. In particular, cross-section data ignore the time dimension, while time series data of market averages (indices) confound any existing company-specific effects. Because panel data contain more information, the power of the tests based on them will be significantly increased relative to similar tests based on only cross-section or time series models.

We have tackled this important question of return predictability in the short run (contemporaneous and lags), in the presence of asymmetric effects (quantile regression). We do it comprehensively to encompass both fundamentals as well as contagion variables, and to search the entire distribution of returns.

There is a general consensus that expected returns are notoriously difficult to predict, and the reader should be aware that reaching general conclusions about the predictability of returns is not a straightforward endeavor. Consequently, the literature provides ample evidence of conflicting findings. Here, we are not trying to model price changes per se, our focus is to analyze the relationship between percentage changes in fundamentals and contagion variables, and percentage changes in stock prices.

A key issue to test the existence of bubbles is the idea of fundamental value. Hamilton (1986) and Tirole (1985), among others, proposed that the value of a financial asset is the present value of its future payoffs. Shiller (1981) suggested that one can use either dividends or earnings to evaluate these future payoffs. In contrast to most prior bubble research where dividends are used to proxy cash flows, our perspective is that, in the long run, any corporate payoffs can only be made from revenues. If during a sustained period of time stock prices grow at a rate significantly different from that of the operating revenues, the moment will come when the market clearing prices will no longer reflect the present value of discounted cash flows. With this idea in mind we proposed twelve different proxies for fundamentals that use accounting data to test Hypotheses 1.

In order to address the possible inefficiency created by short-horizon speculation, we examined the contemporaneous relationship between changes in prices and changes in volume, money flow, and volatility to test Hypothesis 2. We chose these variables because noise trader models propose a causal relation between each of these variables and stock returns (DeLong, Shleifer, Summers, and Waldmann, 1990).

Even though, just as in much of the literature, we find some evidence of a contemporaneous statistically significant relationship between changes in security prices and changes in the fundamentals, we do not reject our Hypothesis 1. The main reason is that our findings are not consistent across OLS, panel data analysis (conditional mean models), and quantile regression (semiparametric), which makes us strongly suspect that the results obtained with the first two methodologies (mean models) are spurious. The reported significance could be mainly the result of the assumptions of the methodologies themselves.

In general, most of our findings using OLS and panel data on fundamentals are consistent with those of other authors: our coefficients are small, and the R^2s close to zero. Lev (1989), for example, suggests that R^2s in earnings-returns regressions are "too low" to be economically relevant. In addition, other researchers propose that the average explanatory power of market models is quite modest (whether it is a single or multiple factor model), even if for some specific firms it is extremely large. Also, those who have taken into account the effect of news on returns point out that this does not seem to materially increase the R^2s (Roll, 1988).

An explanation for the low explanatory value of the fundamental variables, is that prices may respond to information that is leaked throughout the quarter. Easton (1992) suggested that earnings would not be a perfect summary of events of the corresponding return interval. That is because (1) value-relevant events observed by the market (and captured in returns) in the prior period may affect accounting earnings in the current period and (2) value relevant events observed by the market in the current period may not be reported in accounting earnings of the current period. Another explanation provided by authors who looked into the forecasting accuracy of analysts in the short-run horizon, is analyst over optimism of expectations, particularly associated with high forecast earnings growth, low book-to-price ratio, and high past sales growth (Frankel and Lee, 1996) (Harris, 1999).

In reference to the contagion proxies, our three variables are found highly significant across all methodologies. Therefore, we do not reject Hypothesis 2. Our results in this section are consistent with those of other authors who identified a positive relationship between returns and volume, money flow, and volatility. The explanation is that trading strategies pursued by noise traders cause stock prices to move, and noise traders use positive feedback trading strategies. Also, herd behavior explains some of the excessive stock market volatility because a large group trading in the same direction will magnify price shocks (Beaver, 1968) (Clark, 1973) (Epps and Epps, 1976) (Smirlock and Starks, 1988) (DeLong, Shleifer, Summers, and Waldmann, 1990) (Scharfstein and Stein, 1990) (Gallant, Rossi, and Tauchen, 1994).

Our finding about the incremental explanatory value of the variables for greater positive price changes (higher quantiles and Pseudo-R^2) is consistent with two theories. First, the idea that noise traders follow feedback rules and buy when others buy (DeLong et al., 1991) (Chiarella, 1992). Second, with the informational price theory, which explains how some agents derive information from the new price levels that result from the trade by agents who purchase information. In light of volume or price information, agents will disregard their own private information and follow the behavior of the majority (Graham, 1999).

Beaver (1968) proposes an additional explanation for the positive relationship between volume and variability. His idea is that because willingness to pay is greatest for optimistic investors and because trading activity arises from an increase in the divergence of opinion among investors, greater trading tends to occur with price increases. It has also been argued that trading is repressed for bad news information events because the cost of short-selling common shares is greater than purchasing.

Taken together, the findings of this paper seem to support the suggestions of different authors that changes in financial asset prices can be better explained by behavioral factors resulting from contagion of opinion, than by earnings information (i.e. Shiller and Pound, 1986).

In understanding how these results fit in the literature, one should be aware that our findings are not directly comparable with those obtained by authors who used dividends versus earnings, levels rather than returns, indices instead of panel data, or different interval period data. Thus, we are limited in trying to generalize our findings.

If financial asset prices deviate from fundamentals, as suggested by the quantile results, such distortions could affect investment decisions and capital allocations. Predictability of returns has consequences for asset price behavior and one may want to calculate these explicitly. The issue of whether bubbles affect investment spending and the relationship between the statistical versus economic significance of these decisions have not been addressed in this paper. These topics are left for future research.

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