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Fads or bubbles?

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Abstract. This paper tests between fads and bubbles using a switching regression to distinguish between competing models. Two main features of the bubbles model distinguish it from the fads model. First, the bubbles model implies that returns are drawn from regimes which differ in the way returns vary with deviations from fundamental prices. Second, the bubbles model implies that deviations from fundamental price will help predict regime switches. Using US data for 1926–89, we find evidence which is consistent with the fads model even when we allow for variation in expected dividend growth rates and expected discount rates. However, the restrictions which the fads model implies for a more general switching-regression specification are rejected. The rejections point in the direction of the bubbles model, although not all of the implications of the bubbles model are supported by the data.

Key words: macroeconomics and financial markets, fads, bubbles, time series econometrics, regime switching

JEL classification: G1, E3, C3.

Introduction

Events of the last five years, but particularly the terrific rise and fall in the value of "dot-com" shares from 1998 to 2001, have again challenged the view that

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most stock price movements are justified by news about the fundamental value of the underlying firms. This view continues to attract widespread attention despite its ongoing failure to provide coherent explanations for notable market upheavals, such as the 1987 global stock market crash. Furthermore, while there are alternative models of stock price determination, there is little consensus on which of these alternatives gives the most realistic description of the ongoing behaviour we observe in financial markets. This in turn reflects the limited work which has been done comparing the performance of such alternative models.

Two of the main alternatives are the fads model proposed by Summers (1986) and the stochastic bubbles model proposed by Blanchard and Watson (1982). In a world with fads, Cutler, Poterba, and Summers (1991) show that a measure of the deviation of actual price from fundamental price will predict returns. Stochastic bubbles, on the other hand, can lead to regime switching in stock market returns. In this paper, we seek to compare these two alternatives to determine which is more important in describing "non-fundamental" behaviour in stock markets.

We begin by showing that both models can be nested within a switching-regression specification. Each model has testable implications for the switching regression. Using long series from the CRSP database, we find evidence that there is more than just fads in the data. First, regime switches are predictable using a measure of apparent deviations from fundamentals. Second, expected returns (conditional on the size of the deviation in the previous period) are higher in the survival regime than in the collapse regime. The first aspect is quite pronounced and contributes strongly to the rejection of the fads model restrictions. The second aspect is considerably weaker and would not, on its own, lead to the rejection of the fads model restrictions in most of the specifications we consider.

A problem with estimating both fads and bubbles models is that there is no consensus on the correct model of fundamentals. To check the robustness of our results, we use three different techniques for measuring the apparent deviation from fundamentals, each of which is based on successively less restrictive assumptions. For the most part, the qualitative results are similar, regardless of the measure we use.

Our paper is organized as follows. Section I surveys the literature on non-fundamental models of stock prices which is most relevant to this paper. Section II gives a detailed specification of the fads model, then introduces the bubbles model and shows how it leads to a switching-regression specification for stock market returns. Section III discusses estimation of the two models and shows how they imply different parameter restrictions on a general switching-regression specification. Sections IV and V present empirical results for the fads and bubbles models, respectively. Section VI discusses the interpretation of the empirical results and suggests some possible directions for future research.

I. Literature survey

As noted in the survey by Bollerslev and Hodrick (1995), there has been considerable ongoing academic interest in models of the stock market in which price deviates from fundamental price. Some, such as DeLong, Shleifer, Summers, and Waldmann (1989, 1991) argue that presence of a few irrational traders in the market should have important and persistent effects on overall market behaviour. Some, such as Froot and Obstfeld (1991), have argued that apparent deviations from fundamentals may reflect an unexpected non-linearity in the determination of stock prices.

One of the most notable strands in this literature is perhaps that which focusses on the ability of apparent deviations from simple measures of fundamental prices to predict future returns, particularly over long horizons. Summers (1986) points out that if there are fads in the stock market, we may observe long temporary price swings which can be modeled as a slowly decaying stationary component in prices.[1] The decay over time in the transitory component will lead to mean reversion in stock prices. Influential papers documenting this characteristic include Summers (1986), Campbell and Shiller (1987, 1988), Fama and French (1988b) and Cutler, Poterba, and Summers (1991). These papers vary somewhat in the terms used to describe this phenomenum and they focus more on characterizing this apparent behavior of stock prices than in providing a rigorous theoretical underpinning for it. We follow Summers in refering to this behaviour as "fads" and we review its behavior in more detail below. For now, we simply note that in a world with fads, a measure of the deviation of actual price from fundamental price will help predict future returns.

Perhaps the most durable approach to thinking about non-fundamental movements in stock prices is one which is based on the idea of rational agents and multiple expectational equilibria. Such phenomena are frequently referred to as "bubbles" and the origins of such models date back almost as far as the creation of organized financial markets. Rigorous treatments of such behaviour in a rational expectations framework also dates back to early in the tradition of rational expectations modelling, with important contributions by Blanchard (1979), Blanchard and Watson (1982), Tirole (1982, 1985), Obstfeld and Rogoff (1983, 1986) and Diba and Grossman (1988a,b).

It should be noted that many of these articles debated whether bubbles were strictly admissible in a rigorous and fully-rational model. Blanchard and Fischer (1989, p. 238) argue that "[These restrictions] often rely on an extreme form of rationality and are not, for this reason, altogether convincing. Often bubbles are ruled out because they imply, with a very small probability and very far in the future, some violation of rationality, such as non-negativity of prices or the bubbles becoming larger than the economy. It is conceivable that the probability may be so small, or the future so distant, that it is simply ignored by market participants." Moreover, work by Allen and Gorton (1991) and Leach (1991) has shown that restrictions on non-fundamental solutions are not robust to minor changes in assumptions, such as heterogeneous agents and either continuous time or more than two periods in an OLG model.

Our motivation for using the models of speculative behaviour in this paper is the same as Solow (1957, p. 323–324) in using an aggregate production function, which was controversial at the time: "Either this kind of [approach] appeals or it doesn't.... If it does, I think one can draw some ... useful conclusions from the results."

The existence of multiple equilibria in theoretical models has been linked to empirical evidence of regime switching in studies ranging from Lee and Porter

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[1] The predictability of returns could come from time variation in required returns. Fama (1991), Fama and French (1988b), and Poterba and Summers (1988) discuss the question of interpretation in more detail and provide references to a variety of explanations.

(1984) to Jeanne and Masson (2000). The assumption in most bubble models that a bubbles may either survive or collapse implies that stock market returns come from two distinct regimes, one of which corresponds to surviving bubbles and the other to collapsing bubbles. The bubbles model therefore implies that the relationship between returns and deviations from fundamental price will differ between the two regimes. This observation has lead many researchers to test for evidence of bubbles by testing for certain kinds of regime switching. The multivariate approach we describe below is similar to that used in van Norden and Schaller (1993), van Norden (1996), and Schaller and van Norden (1997a, 1999). An alternative univariate approach has been suggested by Funke, Hall and Sola (1994), and Hall, Psarakakis, and Sola (1999); see van Norden and Vigfusson (1998) for an overview and comparison.

II. Specification of fads and bubbles models

As the above discussion suggests, the fads and bubbles strands in the empirical literature have remained largely distinct. Our aim in this paper to combine both in a more general framework and examine which best characterizes the observed behaviour of stock prices. This requires that we first review the specifications of both models in more detail.

A. The fads model

The following model, used in Fama and French (1988) and Cutler, Poterba, and Summers (1991), can capture both the traditional efficient-markets model and the idea of fads:

$$p_t = p_t^* + e_t \tag{1}$$

$$p_t^* = p_{t-1}^* + \varepsilon_t \tag{2}$$

where p_t is the log of the stock market price in period t, p_t^* is the non-stationary component of the log price, and ε_t is white noise. Under the traditional model, log prices are a martingale, $e_t = 0$ and returns (the difference in log prices) are white noise.[2] We can think of p_t^* as the fundamental price because it does not include a fads element. Under the fads model, prices have a stationary component:

$$e_t = \rho_e e_{t-1} + v_t \tag{3}$$

Thus the fads model can be characterized as a situation in which $\sigma_e^2 > 0$ and $\rho_e > 0$, where σ_e^2 is the variance of e_t. The stationary component e_t in stock prices implies that returns will be predictable.

Cutler, Poterba, and Summers (1991) consider a situation in which a proxy is available for the fundamental price. Because there is no universally accepted

[2] Strictly speaking, efficiency in financial markets implies that log prices are a martingale, rather than a random walk. Our presentation of the traditional and fads models follows Cutler, Poterba, and Summers (1991). Later in this section we allow the variance of ε_t to vary over time; then in the traditional model (i.e., when $\sigma_e^2 = 0$) log prices are a martingale.

model of fundamentals, any such proxy is likely to be measured with error. We can model this using an errors-in-variables approach:

$$p_t^f = p_t^* + w_t \tag{4}$$

where p^f is the proxy and w is the measurement error (which is assumed to be serially uncorrelated). Cutler, Poterba, and Summers also suggest the following statistic λ as a way of reflecting the degree of measurement error:

$$\lambda \equiv \frac{\sigma_e^2}{[\sigma_e^2 + \sigma_w^2]} \tag{5}$$

If p^f is a perfect measure of fundamentals (so $\sigma_w^2 = 0$), then $\lambda = 1$; if p^f measures p^* with error, then $\lambda < 1$. In any case, since it is a ratio of variances it is always non-negative.

To see how fads lead to the predictability of returns based on lagged information, use equations (1)–(4) to express returns in terms of differences between the price and the proxy for fundamental price. This suggests regressions of the form:

$$p_{t+1} - p_t = \beta_0 + \beta_b(p_t - p_t^f) + v_{t+1} \tag{6}$$

where $p_{t+1} - p_t$ (the difference in log prices) is the rate of return and $p_t - p_t^f$ is the difference between actual (log) price and a measure p_t^f of the fundamental (log) price.

One example of a proxy for fundamental price is the log of the real dividend. (This is the proxy that Cutler, Poterba, and Summers (1991) use in their empirical work on stock market returns.) Equation (6) is then a regression of returns on the lagged log dividend-price ratio. It is easy to show that (1)–(4) imply that:

$$\operatorname*{plim}_{T\to\infty}(\hat{\beta}_b) = -(1 - \rho_e)\lambda \tag{7}$$

The fads model therefore implies that estimates of β_b should be negative.[3]

In section III, we will show that this fads model represents a special case of a general switching-regression specification. In the same section, we will discuss how to estimate and test the fads model.

B. The bubbles model and regime switching

In this section, we begin by describing the Blanchard-Watson (1982) model of stochastic bubbles. We then follow Schaller and van Norden (1999) in showing how this can fit within the framework of a switching regression.

By stochastic bubbles, we mean bubbles which may either survive or collapse in each period. The existence of stochastic bubbles implies that there are

[3] Equations (6) and (7) correspond to equations (6) and (7) in Cutler, Poterba, and Summers (1991).

two regimes generating stock market returns, one where the bubble collapses and one where it survives. Rational investors take this into account when deciding whether or not to hold an asset. The period-to-period arbitrage condition allows us to impose some structure on asset returns in the surviving and collapsing regimes: in the surviving regime, returns should be sufficiently high to compensate the investor for the possibility that the bubble may collapse. Combined with the historical observation that larger overvaluations are more likely to collapse, this provides us with the essential elements for a regime-switching specification for stock market returns.

We begin by considering a simple asset-pricing model where risk-neutral investors choose between holding an asset that yields $(1 + r)$ and a risky stock. The investors' first-order conditions imply:

$$P_t = (1 + r)^{-1} \cdot (E_t(P_{t+1}) + D_t) \tag{8}$$

where P_t and D_t are the stock's price and dividend at time t and E_t denotes the expectation conditional on information available at time t. One possible solution to this equation defines the fundamental price

$$P_t^* \equiv \sum_{k=0}^{\infty}(1 + r)^{-(k+1)} \cdot E_t(D_{t+k}) \tag{9}$$

All other prices are said to be "bubbly," with the size of the bubble defined as

$$B_t \equiv P_t - P_t^* \tag{10}$$

Since we have assumed that all asset prices, bubbly or not, follow (8), this implies that the bubble must satisfy the condition

$$E_t(B_{t+1}) = (1 + r) \cdot B_t \tag{11}$$

Blanchard (1979) and Blanchard and Watson (1982) consider a particular stochastic solution to (11). They suppose there are two states of nature, one where the bubble survives (state S) and one where it collapses (state C). If the possibility of being in state S is some constant q and being in state C implies $B_t = 0$ then (11) implies

$$E_t(B_{t+1}|S) = \frac{(1 + r)}{q} \cdot B_t \tag{12}$$

The intuition here is that (if $B_t > 0$) agents expect capital losses of B_t in state C, which must be balanced by expected capital gains in state S in order to earn the required rate of return on the bubble.

Historical accounts suggest that the probability of a bubble surviving decreases as the bubble grows. The Blanchard-Watson model can therefore be extended by allowing the probability of survival q to depend on the proportionate size of the bubble

$$q \equiv q(b_t) \tag{13}$$

where $b_t \equiv B_t/P_t$ and

$$\frac{dq(b_t)}{d|b_t|} < 0 \tag{14}$$

Note the use of the absolute value of b_t, since the bubble may be positive or negative.

While some notable market crashes have occurred in a single day, in other cases a collapse may occur over several months.[4] To model this, the Blanchard-Watson model is again generalized to permit the expected value of the bubble, conditional on collapse, to be non-zero, thereby allowing for partial collapses.[5] Assuming that the expected size of a bubble in state C, which we define as $u_t P_t$, depends on the relative size of the bubble in the previous period, so

$$E_t[B_{t+1}|C] = u(b_t) \cdot P_t \tag{15}$$

Further assuming that $u(\dot{})$ is a continuous and everywhere differentiable function and that:[6]

$$u(0) = 0 \tag{16}$$

$$0 \leq \frac{du(b_t)}{db_t} \leq 1 \tag{17}$$

(The differentiability assumption is made because we will need to linearize the model.) The assumptions (16) and (17) are added to ensure that a collapse means that the bubble is expected to shrink.[7] Imposing (16) then gives

$$E[B_{t+1}|S] = \frac{1+r}{q(b_t)} B_t - \frac{1-q(b_t)}{q(b_t)} u(b_t) \cdot P_t \tag{18}$$

This shows that the expected value of the bubble in the surviving state is a decreasing function of the probability of survival $q(b_t)$. In other words, the greater the probability of collapse, the larger the gain on a positive bubble must be in the surviving state in order to compensate the investor for the possibility of collapse.

Note that when $q(b_t) \equiv q$, a constant, and $u(b_t) \equiv 0$, this model reduces to the Blanchard-Watson process.

It is straightforward to derive the expected excess returns R in each regime,

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[4] The fall in the Tokyo stock exchange in the period following January 1990 or in the NASDAQ after mid-2000 are examples.

[5] Early papers which considered bubbles which either shrink (or partially collapse) include Diba and Grossman (1988b) and Evans (1991).

[6] As with assumptions on $q(b_t)$, the assumptions on $u(b_t)$ are not imposed on the data. Instead, they allow us to determine the expected signs and relative magnitudes of the parameters.

[7] To see this, draw a graph with $u(b_t)$ (which equals $E[B_{t+1}|C]/P_t$) on the vertical axis and b_t on the horizontal axis. The function $u(b_t)$ passes through the origin, since $u(0) = 0$. The 45° line represents a situation where $E[B_{t+1}|C]/P_t = B_t/P_t$; i.e., where a "collapsing" bubble is the same size as the previous period's bubble. Since $0 \leq u' \leq 1$, $u(b_t)$ always lies on or below the 45° line. Thus these assumptions ensure that a collapsing bubble is no larger than the bubble in the previous period.

where excess returns are the rate of return on the bubbly asset less the rate of return on the alternative asset.

$$E_t(R_{t+1}|S) = \frac{1-q(b_t)}{q(b_t)}[(1+r)b_t - u(b_t)] \tag{19}$$

$$E_t(R_{t+1}|C) = u(b_t) - (1+r)b_t \tag{20}$$

Noting that conditional expected excess returns are a function of b_t, we can take first-order Taylor series approximations of $E_t(R_{t+1}|S)$ and $E_t(R_{t+1}|C)$ with respect to b_t around some arbitrary value $\bar{b}$ to obtain:

$$E(R_{t+1}|S) = \beta_{SO} + \beta_{Sb}b_t \tag{21}$$

$$E(R_{t+1}|C) = \beta_{CO} + \beta_{Cb}b_t \tag{22}$$

where

$$\begin{aligned}\beta_{Sb} \equiv & -\frac{1}{q(\bar{b})^2}\cdot\left.\frac{dq(b_t)}{db_t}\right|_{b_t=\bar{b}}\cdot[(1+r)\cdot\bar{b} - u(\bar{b})] \\ & + \frac{1-q(\bar{b})}{q(\bar{b})}\cdot\left[1+r-\left.\frac{du(b_t)}{db_t}\right|_{b_t=\bar{b}}\right]\end{aligned} \tag{23}$$

$$\beta_{Cb} \equiv \left[\left.\frac{d_u(b_t)}{db_t}\right|_{b_t=\bar{b}} - (1+r)\right] \tag{24}$$

Assuming $r \geq 0$, we can then prove that $\beta_{Sb} \geq 0$ and $\beta_{Cb} \leq 0$, and more generally that $\beta_{Sb} \geq \beta_{Cb}$.[8]

By dropping the expectations operator E_t in equations (21) and (22), we can rewrite them as

$$R_{S,t+1} = \beta_{SO} + \beta_{Sb}\cdot b_t + \varepsilon_{S,t+1} \tag{25}$$

$$R_{C,t+1} = \beta_{C0} + \beta_{Cb}\cdot b_t + \varepsilon_{C,t+1} \tag{26}$$

where $\varepsilon_{i,t+1} \sim N(0,\sigma_i)$ for $i = S, C$. To complete the switching-regression model, we need a functional form for $q(b_t)$ which satisfies (14) and which guarantees that the resulting estimates of q will be bounded between 0 and 1. We use the Logit form

$$q(b_t) = \Phi(\beta_{q0} + \beta_{qb}b_t^2) \tag{27}$$

where Φ is the logistic cumulative distribution function. These three equations

[8] The proof for β_{Cb} follows directly from (24). For β_{Sb}, we can use (23) and the fact that $1 \geq q(b_t) \geq 0$ to show that the second term in the expression is always non-negative. Equations (14), (16), and (17) together imply that the first term is also non-negative, so the sum of the two terms will be non-negative.

(25 to 27) form a standard switching-regression model of the type described by Goldfeld and Quandt (1976) and Hartley (1978), and can be estimated by standard maximum likelihood methods.[9] Previous empirical studies of this type include van Norden and Schaller (1993), who examined returns on the Toronto Stock Exchange, and van Norden (1996), who used a similar framework to test for bubbles in foreign exchange markets.

III. Testing the fads & bubbles models

In this section, we show how both the fads and bubbles models nest within and imply parameter restrictions on the general switching-regression specification above. By testing these restrictions jointly and separately, we can make statements about the ways in which each model corresponds, or fails to correspond, to the data.

The fads model implies a number of restrictions on the general switching-regression specification. First, according to the fads model, expected returns (conditional on b_t) should be the same in both regimes. This implies that β_{S0} should equal β_{C0} and that β_{Sb} should equal β_{Cb}. Second, as shown in section I, the fads model implies that returns should be mean reverting. This implies that the estimated value of β_b should be negative. Finally, according to the fads model, b_t should not influence which regime will occur in the subsequent period. This implies that β_{qb} should equal zero. The fads model restrictions can be summarized as follows:

$$\beta_{S0} = \beta_{C0} = \beta_0 \tag{28}$$

$$\beta_{Sb} = \beta_{Cb} = \beta_b \tag{29}$$

$$\beta_{qb} = 0 \tag{30}$$

$$\beta_b < 0 \tag{31}$$

With these restrictions on the switching regression, the fads model differs from a linear regression in only one respect; the variance of the error term may change with the state.[10] The fads model is silent on the question of whether returns should be homoscedastic or heteroscedastic. We decided against im-

[9] For those familiar with Markov switching models, it may be useful to note that this switching model has a related stochastic structure. A two-state Markov switching model has two state-dependent probabilities: $q(t) = \Pr(S(t) = 0 \mid S(t-1) = 0)$ and $p(t) = \Pr(S(t) = 1 \mid S(t-1) = 1)$. The switching model presented here has one state-independent probability $q(t) = \Pr(S(t) = 0)$. This is the special case of the Markov switching model where $q(t) = 1 - p(t)$; i.e., the probability of today's state is independent of yesterday's state. Our specification implies that volatility will be independently distributed between a high and low variance state. However, there is much evidence that stock market volatility shows persistence; that is, periods of high volatility are more likely to be followed by high volatility than are periods of low volatility. For example, see Schwert (1989), who considers a Markov-switching model for stock market variances.

[10] Kim and Kim (1996) also estimate a model of fads which allows for regime-switching in the variance of returns. They find evidence of fads, particularly around the first oil shock and the 1987 crash. Their approach differs substantially from ours in that they do not include any measure of $(p_t - p_t^f)$, the difference between actual and fundamental price, in their specification.

posing the homoscedasticity assumption for two reasons. First, imposing this assumption might result in our rejecting the fads model simply because the switching regression finds significant heteroscedasticity in the data. Second, imposing the homoscedasticity assumption would greatly complicate testing the fads model against the general switching-regression specification alternative since the parameter β_{q0} would be unidentified under the null hypothesis of fads.[11]

We can test the fads model in two basic ways. The first way is to impose the first three restrictions and compare the fit of the resulting regression with the fit of the unrestricted general switching-regression specification. In section IV, we use a likelihood ratio statistic to conduct this joint test.[12] The second way is to impose the first three restrictions (so we are estimating the fads model) and check whether β_b is negative.

The bubbles model also has implications for the general switching-regression specification. First, according to the bubbles model, expected returns (conditional on b_t) should be greater in the states where the bubble survives than in the states where it collapses.[13] This implies that β_{S0} will not necessarily equal β_{C0} and that β_{Sb} should be greater than β_{Cb}. Second, according to the bubbles model, collapses are more likely when bubbles are large in magnitude. This implies that β_{qb} should be positive. The implications of the bubbles model for the general switching-regression specification can be summarized as follows:

$$\beta_{S0} \neq \beta_{C0} \tag{32}$$

$$\beta_{Sb} > \beta_{Cb} \tag{33}$$

$$\beta_{qb} > 0 \tag{34}$$

There are two main ways in which we can test the bubbles model against the fads model. The first we have already discussed above. The fads model implies certain restrictions on the general switching-regression specification. These restrictions are inconsistent with the bubbles model, so if we fail to reject them, we would conclude that there is no significant evidence for the bubbles model. The second sort of test involves the implications which are summarized in the previous three equations. If these parameter restrictions hold, it provides evidence in favour of the bubbles model.[14]

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[11] See Hansen (1996) for a discussion of hypothesis testing under these conditions.

[12] A number of authors have noted that while Lagrange Multiplier and Wald tests should be asymptotically equivalent to the LR tests, they sometimes give widely divergent results when applied to regime switching models. For example, see Engel and Hamilton (1990). The LR tests are thought to be the most reliable, so we use these for most of the joint hypothesis tests we report.

[13] For $b_t < 0$, the expected returns in the surviving regime should be larger in absolute value (i.e., more negative) than those in the collapsing regime. Of course, the implications for the signs of β_{Sb} and β_{Cb} are the same regardless of whether b_t is positive or negative.

[14] As always, other interpretations, which may involve neither bubbles nor fads, are possible. One particularly interesting study is Driffill and Sola (1998), who consider both "intrinsic bubbles" [Froot and Obstfeld (1991)] and regime switching in dividends. They find that each can account for the main movements in stock prices in the U.S. over the period 1900–87, although a specification which allows for regime switching in dividends (but no bubble) is rejected in favour of a specification which includes both regime switching in dividends and a bubble.

The data we examine for evidence of speculative behaviour is drawn from the Center for Research on Security Prices (CRSP) database. We use the monthly value-weighted price (P) and dividend (D) indices for all stocks from January 1926 to December 1989. R_t is constructed as the difference between gross nominal returns (including dividends) and the monthly yield on Moody's Industrial Bond Index. Since dividends display strong seasonal fluctuations, we follow Fama and French (1988a) in using an average over the twelve-month period ending in the given month to deseasonalize D. Where required for constructing fundamental values, we convert nominal values to real using the Consumer Price Index.

IV. Empirical estimates of the fads model

The fads model is a switching regression of the form:

$$R_{t+1} = \beta_0 + \beta_b \cdot b_t + \varepsilon_{i,t+1}$$

$$\varepsilon_{i,t+1} \sim N(0, \sigma_i), \quad i = S, C$$

$$\Pr(i = S) = \Phi(\beta_{q0})$$

Specifically, this is a standard switching-regression model of the type described by Goldfeld and Quandt (1976) and Hartley (1978), and can be estimated by standard maximum likelihood methods. Given normality of $(\varepsilon_{S,t+1}, \varepsilon_{C,t+1})$, estimates of the β's can be found by maximizing the likelihood function

$$\prod_{t=1}^{T} \left[\Phi(\beta_{q0}) \cdot \varphi\left(\frac{R_{t+1} - \beta_0}{\sigma_S}\right) \cdot \sigma_S^{-1} \right.$$
$$\left. + \{1 - \Phi(\beta_{q0})\} \cdot \varphi\left(\frac{R_{t+1} - \beta_0}{\sigma_C}\right) \cdot \sigma_C^{-1} \right] \tag{35}$$

where φ is the standard normal probability density function (pdf) and σ_S, σ_C are the standard deviations of $\varepsilon_{S,t+1}$, $\varepsilon_{C,t+1}$. This estimation technique takes b_t, which we construct separately, as given. (The construction of b_t is discussed below.)

We use three different approaches to measuring b_t, the proportional derivation of actual stock market price from fundamental price. To motivate the three approaches, consider the classic Gordon (1962) model:

$$P_t = \frac{D_t}{r - g} \tag{36}$$

where g is the dividend growth rate. We can think of the fundamental price in the Gordon world as a function of current dividends, anticipated dividend growth, and anticipated interest rates.

The first measure of the deviation of actual stock market price from fundamental price (b^A) is based on a multiple of current dividends, where the multiple is the sample mean of the price-dividend ratio. The second measure (b^B) is based on a multiple of current dividends plus a multiple of the predicted present value of future dividend changes, where the predictions come from a bivariate VAR of dividend changes and the "spread" (the stock price minus a multiple of current dividends). The third measure is based on $\exp(-\delta_t^c)$ times current dividends, where δ^c is the predicted log dividend-price ratio, where the predictions come from a VAR involving the log dividend-price ratio, the interest rate, and the growth rate of dividends. (These three approaches to measuring b_t are described in more detail in an appendix which is available from the authors.)

A. Assuming the dividend process (b^A)

Table I presents estimates of the fads model. We begin by focusing on the first column of the table which presents parameter estimates based on b_t^A. A major implication of the fads model is that a regression of returns on the apparent deviation of actual prices from fundamental prices should yield a negative coefficient. As the first column shows, the point estimate of this coefficient (denoted β_b) is -0.013 and the t-statistic is -2.1, a result which is consistent with the fads model.[15] To get a sense of the economic significance of the point estimate, consider the value of b_t in September 1987 (one of the larger values in the sample and one of historical interest). With $b_t = .29$, the point estimate implies excess returns will be lower by .37% per month (5% per year).

The result for β_b is consistent with the results of previous studies. As noted above, the regression reported in the first column of Table I is very similar to the Cutler, Poterba, and Summers (1991) test of the fads model. Their estimate of β_b is -0.01 which is close to our estimate.[16]

A number of authors have argued that the evidence of fads is weaker if one takes account of heteroscedasticity. For example, Kim, Nelson, and Startz (1991) argue that most of the evidence for mean reversion comes from the period before World War II, a period during which the volatility of stock market returns was unusually high.[17] We allow for heteroscedasticity by letting disturbances come from a high and low variance regime. As Table I shows, σ_C is about three times as large as σ_S, so heteroscedasticity appears to be a genuine issue in the data.[18] Even after allowing for heteroscedasticity, there is still evidence that returns are predictable, since the results in column one of Table I show β_b to be significantly negative.

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[15] We report t-ratios based on the inverse of the Hessian. The results that we report are asymptotically consistent and efficient under our assumptions. A number of recent studies [e.g., Kim, Nelson, and Startz (1991), McQueen (1992), Nelson and Kim (1993), and Richardson and Stock (1989)] have found that standard test statistics can be misleading in studies of stock market predictability. In this paper, we use more than 700 non-overlapping observations and account for conditional heteroscedasticity.

[16] Our results correspond most closely to the last row, first column of their Table 6. The sign of their estimate differs because they regress returns on fundamental price minus actual price and we regress returns on actual price minus fundamental price.

[17] See also McQueen (1992) and Nelson and Kim (1993) on heteroskedasticity.

[18] A formal test for the equality of σ_S and σ_C is difficult; see Hansen (1996) and Garcia (1998) for recent progress in this area.

Table I. The fads model: Full sample (1929–1989)

Coefficients	b_t^A	b_t^B	b_t^C
β_0	0.0067 (4.015)	0.0047 (2.691)	0.0051 (2.988)
β_b	−0.0126 (−2.079)	−0.0117 (−2.122)	−0.0077 (−2.547)
β_{q0}	−1.1983 (−7.511)	−1.1951 (−7.469)	−1.1747 (−7.354)
σ_S	0.0392 (21.198)	0.0393 (20.919)	0.0390 (20.535)
σ_C	0.1278 (8.526)	0.1289 (8.460)	0.1274 (8.574)
Joint Test	16.32 (0.0010)	10.82 (0.0127)	4.02 (0.2598)

The coefficients are estimated from a switching regression of the form

$$R_{t+1} = \beta_0 + \beta_b \cdot b_t + \varepsilon_{i,t+1}$$

$$\varepsilon_{i,t+1} \sim N(0, \sigma_i), \quad i = S, C$$

$$\Pr(i = S) = \Phi(\beta_{q0})$$

The figures in parentheses below the point estimates are t-statistics calculated using the inverse of the Hessian. The headings b_t^A, b_t^B, and b_t^C refer to three different measures of apparent deviations from fundamental price which are described more fully in Subsections A, B, and C of Section IV, respectively. The Joint test takes the general switching-regression specification represented by the equations (25)–(27) as the null hypothesis and the coefficient restrictions in equations (28)–(30) as the alternative hypothesis; the likelihood-ratio statistic is distributed χ^2 with three degrees of freedom. The marginal significance levels (p-values) are in parentheses below the Joint test statistics. The switching regression is estimated using the maxlik procedure in GAUSS with a combination of BFGS and BHHH algorithms. For b_t^A, the sample period is 1927–89, because lagged data are not required for the VAR's (which are used to construct b_t^B and b_t^C).

In section III, we discussed two main types of tests of the fads model. The first imposes the fads model restrictions on the general switching-regression specification – the general switching regression specification is equations (25), (26), and (27) – and then tests whether or not β_b is negative. However, this does not test between the fads and bubbles models. The second type of test examines whether the fads model restrictions – equations (28), (29), and (30) – are valid; it is therefore a more useful test in distinguishing between fads and bubbles.

The fads model imposes restrictions on the general switching-regression specification. These restrictions reflect two key differences between the fads model and the bubbles model. First, the bubbles model implies that returns are drawn from two distinct regimes, so that the intercept (β_{S0} and β_{C0}) and slope (β_{Sb} and β_{Cb}) coefficients may differ between regimes. Second, the bubbles model implies that the size of deviations from fundamental price influence the regime from which each stock market return is drawn, so that β_{qb} will not be equal to zero.

As shown in the lower portion of Table I, the likelihood-ratio test statistic for the joint test of the fads model restrictions is 16.3. Since this test has a χ^2 distribution with three degrees of freedom under the null hypothesis of fads, the joint test strongly rejects the fads model restrictions.

B. Alternative measures of deviations from fundamental price (b^B, b^C)

Constructing a measure of the fundamental stock market price is an inherently difficult and potentially contentious task. If we were attempting to test either the fads model or the bubbles model against the null hypothesis that stock market returns are driven exclusively by fundamentals, it would also be an extremely important task. When we are trying to distinguish between the fads model and the bubbles model, it is less clear that our choice of a model of fundamentals is crucial.

Cutler, Poterba, and Summers (1991) argue that a noisy measure of fundamental price will tend to bias tests against finding evidence that non-fundamentals are important. Thus, if we use a noisy measure of fundamental price and still find evidence of either fads or bubbles, their view is that the noisiness of our measure of fundamentals strengthens the case that non-fundamentals matter. Others take a different view. For example, Cecchetti, Lam, and Mark (1990) argue that some of the evidence for fads can be explained by variations in the endowment process. In the present value model which we outline in section II, this might be represented, for example, by variation in the expected growth rate of dividends.

Whether or not the measure of fundamentals makes a difference in testing between fads and bubbles is a question on which the previous literature is largely silent. Our approach is therefore eclectic and empirical: we consider various measures of fundamental price and examine whether they lead to different results.

The results in the first column of Table I assume that the expected dividend growth rate is constant. Our second measure of fundamental price allows for predictable variation in the dividend growth rate. In particular, it incorporates the information available in past dividend changes and stock market prices using a linear projection on this past information.[19]

We refer to the measure of deviation from fundamental price which incorporates predictable time variation in the dividend growth rate as b^B. The results for this measure are presented in column two of Table I. The point estimate of β_b is -0.012 with a t-statistic of 2.1, which is very close to the results using b^A. We can test the fads model against the bubbles model by determining whether the fads model restrictions on the general switching-regression specifi-

[19] If the existence of fads or bubbles leads returns to be predictable, then incorporating this predictability in the measure of fundamental price might bias tests against finding evidence for fads or bubbles. Whether incorporating this predictability into fundamental price would tend to bias the tests relatively more against fads or against bubbles is hard to say.

cation are valid. In the lower portion of Table I, the test statistic for the joint test of these restrictions is 10.8. As in the earlier results, this is a strong rejection of the fads model restrictions.

Fama (1990) and Fama and French (1988) argue that the predictability of returns is due to time variation in expected returns. One way to take this into account is to use excess returns as the dependent variable, as we do in this paper. This captures variations in the rate of return on the alternative asset. A second way to take this into account is to use predictable variation in discount rates in constructing the measure of fundamental price. This may help to capture predictable variation in the interest rate or the risk premium.

We refer to the measure of deviation from fundamental price which incorporates predictable variation in the discount rate (as well as in the dividend growth rate) as b^C. The results for this measure are presented in column three of Table I. The point estimate of β_b is -0.008 with a t-statistic of 2.5. The value of b_t^c is .51 in September 1987, so the point estimate of β_b implies returns will be about .39% lower in October (about 5% lower at annualized rates). This is very close to the results using b^A.

The second type of test is whether the fads model restrictions on the general switching-regression specification are valid. In the lower portion of Table I, the test statistic for the joint test of these restrictions is 4.0. In contrast to the earlier results, the test fails to reject the fads model restrictions.

We can briefly summarize the results for the full sample. The main focus of this paper is testing between fads and bubbles. We do this by testing the restrictions which the fads model imposes on the general switching-regression specification. For two of our three measures of fundamental price, we find strong rejections of the fads model restrictions. Our estimates of the fads model differ from previous research because we allow for state-dependent conditional heteroscedasticity; nevertheless, we still find evidence that returns are predictable, since our estimates of β_b are negative. The evidence that returns are predictable is also robust to allowing for variation in the dividend growth rate and the interest rate in constructing measures of fundamental price.

C. Subperiods

It is often suggested that much of the evidence for the predictability of returns comes from periods which include the 1929 crash and the Great Depression.[20] More generally, time series econometric results are sometimes sensitive to the specific time period over which the estimation is done. In this subsection, we therefore present results for three subperiods – 1929–45, 1946–72, 1973–89. The first includes the 1929 crash, the Great Depression, and World War II; the second includes the post-war boom up until the first major oil shock; and the third covers the most recent period, including the inflation of the 1970's and the 1987 crash.

The results for the period 1929–45 (Table II) are the most surprising. Once allowance is made for state-dependent heteroscedasticity (as our switching regression does), the evidence for fads is very weak. Contrary to the prediction of the fads model, the estimate of β_b is either positive or close to zero, depending

[20] See, for example, Kim, Nelson, and Startz (1991).

Table II. The fads model: 1929–1945

Coefficients	b_t^A	b_t^B	b_t^C
β_0	0.0085 (1.763)	0.0043 (0.730)	0.0007 (0.090)
β_b	0.0056 (0.405)	−0.0003 (−0.017)	−0.0067 (−0.697)
β_{q0}	−0.7387 (−2.427)	−0.7342 (−2.426)	−0.7508 (−2.301)
σ_S	0.0482 (7.643)	0.0513 (9.034)	0.0517 (7.730)
σ_C	0.1490 (5.993)	0.1538 (5.509)	0.1540 (5.611)
Joint Test	12.65 (0.0055)	5.60 (0.1329)	4.02 (0.2596)

See the notes to Table I. For b_t^A, the sample period is 1927–45, because lagged data are not required for the VAR's (which are used to construct b_t^B and b_t^C).

on how we measure fundamental price. In all cases, the *t*-statistic on β_b is less than one in absolute value.

In the 1946–72 period, the estimates of β_b are all negative and all have *t*-statistics greater than two in absolute value as shown in Table III. However, when we test the fads model restrictions, they are very strongly rejected regardless of which measure of fundamental price we use.

The results for the period 1973–89 provide the evidence most consistent with the fads model. As shown in Table IV, the estimates of β_b are all negative and all have *t*-statistics greater than two. Nevertheless, one of the three measures of fundamental price leads to a rejection of the fads model restrictions.

The subperiod results suggest that the evidence for fads we find in the full sample is not coming primarily from the 1930's; the estimates of β_b are more consistent with the fads model during the post-war boom and the period since the 1973 OPEC shock. However, as in the full sample, the subperiod results frequently reject the restrictions implied by the fads model, suggesting that there is more in the data than fads.

We discuss the interpretation of the empirical results for the fads model (and how they relate to the empirical results for the bubbles model) in the conclusion.

V. Empirical estimates of the bubbles model

In this section, we present estimates of the bubbles model derived in section II as well as tests of the restrictions which the bubbles model implies for the general switching-regression specification. The bubbles model differs from the

Table III. The fads model: 1946–1972

Coefficients	b_t^A	b_t^B	b_t^C
β_0	0.0084 (3.742)	0.0066 (3.065)	0.0057 (2.562)
β_b	−0.0180 (−2.462)	−0.0153 (−2.380)	−0.0092 (−2.480)
β_{q0}	−0.2525 (−0.044)	−0.2925 (−0.057)	−0.1803 (−0.025)
σ_S	0.0338 (2.607)	0.0338 (2.787)	0.0340 (2.209)
σ_C	0.0405 (2.108)	0.0408 (2.139)	0.0398 (1.931)
Joint Test	18.79 (0.0003)	19.09 (0.0003)	17.56 (0.0005)

See the notes to Table I.

Table IV. The fads model: 1973–1989

Coefficients	b_t^A	b_t^B	b_t^C
β_0	0.0044 (1.396)	−0.0010 (−0.296)	0.0246 (2.897)
β_b	−0.0493 (−2.333)	−0.0424 (−2.364)	−0.0711 (−2.781)
β_{q0}	−0.7714 (−1.531)	−0.7795 (−1.573)	−0.6324 (−1.617)
σ_S	0.0360 (8.098)	0.0360 (8.240)	0.0337 (8.983)
σ_C	0.0759 (4.666)	0.0763 (4.681)	0.0741 (5.727)
Joint Test	4.04 (0.2570)	8.38 (0.0388)	1.41 (0.7031)

See the notes to Table I.

fads model in two main ways. First, the bubbles model implies that returns are drawn from two distinct regimes. In particular, we show in section II that the bubbles model implies an inequality restriction on the slope coefficients in the surviving and collapsing regimes, namely that $\beta_{Sb} \geq \beta_{Cb}$. Moreover, since returns come from distinct regimes, there is no reason to expect the intercept coefficients (β_{S0} and β_{C0}) to be the same in the two regimes. Second, the bubbles model implies that deviations from fundamental price influence the regime from which the next period's stock market return is drawn. Specifically, the bubbles model in section II suggests that a bubble is more likely to collapse when the actual price is far away from the fundamental price. This implies that β_{qb} will be positive.

A. Assuming the dividend process

As noted in the previous section, the fads models restrictions are frequently rejected; the estimates of the bubbles model parameters in Table V help us to see why. We begin by focusing on the first column of the table, which presents parameter estimates based on b_t^A. The point estimate of β_{S0} is .0074 with a *t*-statistic of 4.1. If β_{Sb} were zero, this point estimate would translate into positive excess returns of 0.7% per month (9% per year) for a surviving bubble. The point estimate of β_{C0} is $-.0294$ with a *t*-statistic of -1.4. If β_{Cb} were zero, this point estimate would translate into negative excess returns of about 3% per month (31% per year). The point estimates of the intercept coefficients therefore imply substantial differences in expected returns between the surviving and collapsing regimes. The statistical significance of the difference is weaker; as the lower panel of the table shows, the marginal significance level of the restriction $\beta_{S0} = \beta_{C0}$ is about .08.

The bubbles model in section II implies that β_{Sb} should be greater than β_{Cb}. The point estimate of β_{Sb} is $-.0136$ with a *t*-statistic of 2.0. The point estimate of β_{Cb} is $-.0554$ with a *t*-statistic of 1.4. The inequality restriction implied by the bubbles model therefore holds but the point estimates are not sharp enough to reject the null hypothesis that $\beta_{Sb} = \beta_{Cb}$ at conventional significance levels. The economic significance of the coefficient estimates is quite different, though. For example, consider one of the larger values of b_t in our sample, namely the value in September 1929, which was .26. Even at this relatively high value of b_t, the coefficient estimate implies a change in expected returns of only 35 basis points in the surviving regime. In the collapsing regime, the point estimate of β_{Cb} implies a change of 144 basis points.

The bubbles model in section II suggests that bubbles are more likely to collapse when they comprise a large portion of the price of the stock. This implies that β_{qb} should be positive. The point estimate of β_{qb} is 1.71 with a *t*-statistic of 3.1.

The existence of distinct regimes in the bubbles model (and particularly the fact that the probability of a collapse depends on b_t) means that the relationship between returns and b_t can be highly non-linear. One way to illustrate this is to look at the probability that next period's return will be unusually high or low. In the fads model, expected returns next period depend on b_t; thus if b_t is large this period, there is an increased likelihood that next period's returns will be unusually low. In the bubbles model, a change in b_t has an effect through the slope coefficients (β_{Sb} and β_{Cb}), but there is an additional effect because b_t influences the probability that a given regime will occur. Mathematically, the probability of a return two standard deviations below the mean (a "crash") is:

$$\Pr(R_{t+1} < x) = \Phi\left(\frac{x - \beta_{S0} - \beta_{Sb} b_t}{\sigma_S}\right) q(b_t) + \Phi\left(\frac{x - \beta_{C0} - \beta_{Cb} b_t}{\sigma_C}\right)(1 - q(b_t))$$

Table V. The bubbles model: Full sample (1929–1989)

Coefficients	b_t^A	b_t^B	b_t^C
β_{S0}	0.0074 (4.087)	0.0053 (2.818)	0.0059 (3.228)
β_{Sb}	−0.0136 (−1.976)	−0.0117 (−1.926)	−0.0071 (−2.239)
β_{C0}	−0.0294 (−1.402)	−0.0386 (−1.572)	−0.0253 (−1.349)
β_{Cb}	−0.0554 (−1.361)	−0.0757 (−1.553)	−0.0397 (−1.374)
β_{q0}	−1.7660 (−6.181)	−1.6593 (−5.872)	−1.3227 (−4.815)
β_{qb}	1.7132 (3.071)	1.2068 (2.459)	0.2396 (0.800)
σ_S	0.0406 (19.645)	0.0407 (19.812)	0.0394 (18.165)
σ_C	0.1338 (7.463)	0.1340 (7.475)	0.1271 (7.896)
Tests:			
$\beta_{S0} = \beta_{C0}$	3.0284 (0.0818)	3.1647 (0.0753)	2.7031 (0.1002)
$\beta_{Sb} = \beta_{Cb}$	0.9870 (0.3205)	1.6602 (0.1976)	1.2256 (0.2683)
$\beta_{S0} = \beta_{C0}$ and $\beta_{Sb} = \beta_{Cb}$	3.3819 (0.1844)	3.6452 (0.1616)	3.3148 (0.1906)

The coefficients are estimated from a switching regression of the form represented by the equations (25)–(27). The figures in parentheses below the point estimates are t-statistics calculated using the inverse of the Hessian. The headings b_t^A, b_t^B, and b_t^C refer to measures of apparent deviations from fundamental price; see Subsections A, B, and C of Section IV, respectively. The first two tests are based on Wald statistics using the inverse of the Hessian and are asymptotically distributed χ^2, with one degree of freedom. The third test is based on a likelihood-ratio statistic and is asymptotically distributed χ^2 with two degrees of freedom. Marginal significance levels are listed below the test statistics. The estimation uses the max-lik procedure in GAUSS with a combination of BFGS and BHHH algorithms.

The probability of an unusually high return ("rally") can be defined similarly.

If the non-linearity introduced by the bubbles model is empirically important, the magnitude of the fluctuations in the probability of a crash will be much larger in the bubbles model. Figure I graphs the probabilities of a crash generated by the fads and bubbles models. The scale of the fluctuations is very different. For example, from the beginning of the sample to September 1929, the probability of a crash generated by the fads model increases by only about

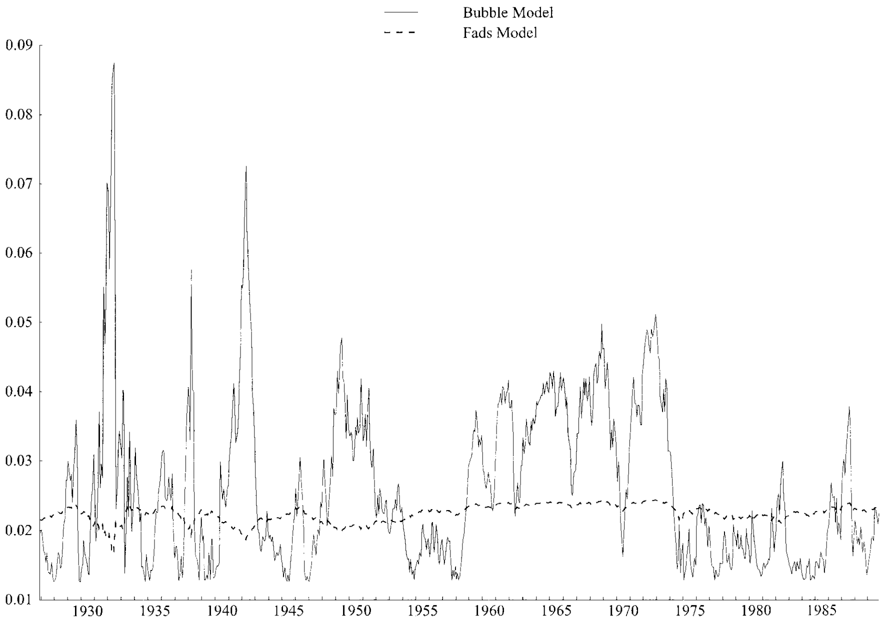

Fig. 1. Probability of a Crash

two-tenths of a percentage point (from .022 to .024). Over the same time span, the probability of a crash generated by the bubbles model rises from about .03 to almost .10. Figure II plots the probability of a rally. In the months leading up to May 1932 (the lowest value of b_t in the sample), the probability of a rally generated by the fads model rises by about one percentage point (from .026 to .036). The probability of a rally generated by the bubbles model rises from about .01 to almost .09.

B. Alternative measures of deviations from fundamental price (b^B, b^C)

The results in the first column of Table V are based on the assumption that the expected dividend growth rate is constant. Our second measure of fundamental price allows for predictable variation in the dividend growth rate. The second column of Table V presents estimates of the bubbles model using b^B. The picture that emerges is broadly similar to the results in the first column of Table V. The point estimate of β_{S0} is positive, while that for β_{C0} is negative and much larger in magnitude. If β_{Sb} and β_{Cb} were zero, the point estimates of the intercept coefficients (β_{S0} and β_{C0}) imply that annualized returns would be about 67% higher in the surviving regime than in the collapsing regime. The marginal significance level for a test of the restriction $\beta_{S0} = \beta_{C0}$ is .08. The point estimate of β_{Cb} is negative and about six times smaller than the point estimate of β_{Sb}. Neither parameter is very precisely estimated, however, so the data fail to reject the restriction $\beta_{Sb} = \beta_{Cb}$. As predicted by the bubbles model in section II, β_{qb} is positive with a t-statistic of about 2.5.

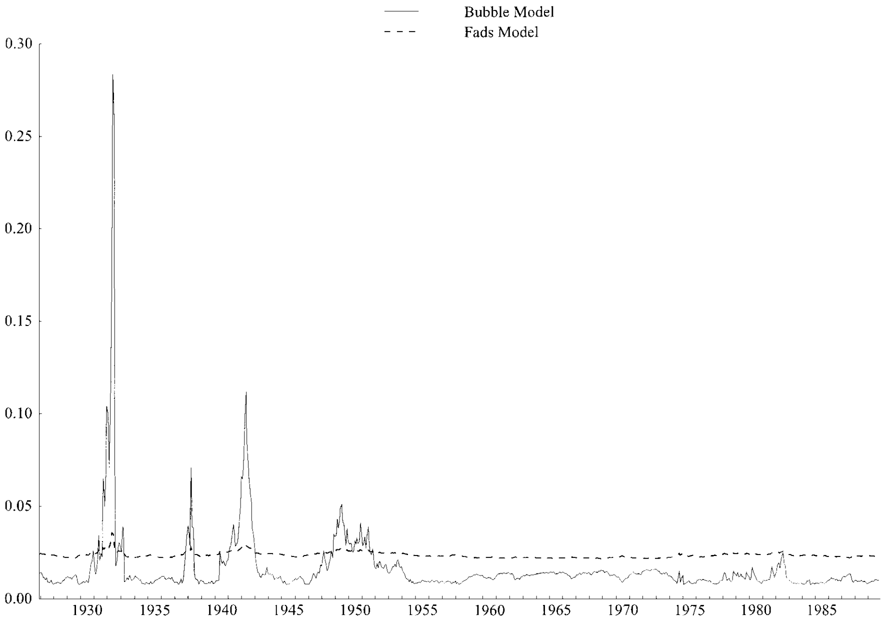

Fig. 2. Probability of a Rally

Our final measure of deviation from fundamental price is b^C which incorporates predictable variation in the discount rate (as well as in the dividend growth rate) in the fundamental price. The results for b^C are presented in column three of Table V. The point estimates of the intercept and slope coefficients in the equations for the surviving and collapsing regimes are similar to those for b^A and b^B. The point estimate of β_{S0} is positive and relatively small in magnitude, while the point estimate of β_{C0} is negative and larger in magnitude. If β_{Sb} and β_{Cb} were zero, the point estimates of the intercept coefficients (β_{S0} and β_{C0}) imply that annualized returns would be about 45% higher in the surviving regime than in the collapsing regime. The marginal significance level for the restriction $\beta_{S0} = \beta_{C0}$ is about .10. As with b^A and b^B, the point estimate of β_{Cb} is negative and smaller than β_{Sb} by about a factor of five. The point estimate of β_{qb} is positive; unlike the estimates of β_{qb} in columns one and two, however, the t-statistic is small.

Intuitively, the bubbles model suggests that: 1) there should be a regime in which the bubble survives and excess returns are positive to compensate the investor for the possibility that the bubble may collapse; 2) in the periods in which a positive bubble collapses, returns should be negative; and 3) the probability of a collapse should increase as the bubble gets larger. The empirical results for the full sample broadly correspond to this description of stochastic bubbles. There is one important exception: simple models of rational bubbles (and the derivations presented in Section II) imply that returns in the surviving regime should be higher when the bubble is larger. This conflicts with our finding that β_{Sb} is negative.

C. Subperiods

For the subperiod which includes the 1929 crash and the Great Depression, the results are broadly similar to those for the full sample. As shown in Table VI, the estimates of β_{S0} are greater than the estimates of β_{C0}, the estimates of β_{Sb} are considerably larger than the estimates of β_{Cb}, and the estimate of β_{qb} is positive. Unlike the full sample, for the period 1929–45, β_{Sb} is either positive or very close to zero.

For the period 1946–72, the estimate of β_{S0} is larger than the estimate for β_{C0} as shown in Table VII. Unlike the full sample, this difference is highly significant; in fact, the difference between β_{S0} and β_{C0} is the main reason the fads model is so strongly rejected during the post-war boom subperiod. The difference in slope coefficients is smaller than in the full sample (and the direction is reversed) and β_{qb} is insignificantly different from zero.

Table VI. The bubbles model: 1929–1945

Coefficients	b_t^A	b_t^B	b_t^C
β_{S0}	0.0110 (1.775)	0.0048 (0.675)	0.0065 (0.372)
β_{Sb}	0.0128 (0.685)	0.0037 (0.217)	−0.0002 (−0.012)
β_{C0}	−0.0427 (−1.297)	−0.0543 (−1.068)	−0.0677 (−1.263)
β_{Cb}	−0.0741 (−1.361)	−0.1046 (−1.232)	−0.0965 (−1.374)
β_{q0}	−1.3388 (−2.773)	−1.3917 (−2.701)	−0.8444 (−0.682)
β_{qb}	1.8821 (2.341)	1.1490 (1.664)	0.1985 (0.239)
σ_S	0.0497 (6.712)	0.0561 (9.065)	0.0510 (2.951)
σ_C	0.1471 (5.231)	0.1676 (4.918)	0.1462 (2.820)
Tests:			
$\beta_{S0} = \beta_{C0}$	2.6087 (0.1063)	1.3002 (0.2542)	2.5374 (0.1112)
$\beta_{Sb} = \beta_{Cb}$	2.1674 (0.1410)	1.5069 (0.2196)	2.1955 (0.1384)
$\beta_{S0} = \beta_{C0}$ and $\beta_{Sb} = \beta_{Cb}$	2.6476 (0.2661)	1.5829 (0.4532)	2.7798 (0.2491)

See the notes to Table V. For b_t^A, the sample period is 1927–45, because lagged data are not required for the VAR's (which are used to construct b_t^B and b_t^C).

Table VII. The bubbles model: 1946–1972

Coefficients	b_t^A	b_t^B	b_t^C
β_{S0}	0.0324 (6.849)	0.0304 (7.146)	0.0296 (7.164)
β_{Sb}	−0.0268 (−2.852)	−0.0237 (−2.824)	−0.0142 (−2.115)
β_{C0}	−0.0013 (−0.300)	−0.0030 (−0.722)	−0.0036 (−0.881)
β_{Cb}	−0.0149 (−1.439)	−0.0132 (−1.264)	−0.0104 (−1.782)
β_{q0}	0.6634 (1.500)	0.5406 (1.351)	0.4315 (1.120)
β_{qb}	−0.3029 (−0.218)	0.1632 (0.151)	0.4462 (0.628)
σ_S	0.0161 (4.784)	0.0161 (4.840)	0.0161 (4.998)
σ_C	0.0382 (17.657)	0.0380 (18.467)	0.0379 (19.116)
Tests:			
$\beta_{S0} = \beta_{C0}$	32.1920 (0.0000)	36.9500 (0.0000)	39.5250 (0.0000)
$\beta_{Sb} = \beta_{Cb}$	0.6562 (0.4179)	0.6187 (0.4315)	0.2066 (0.6494)
$\beta_{S0} = \beta_{C0}$ and $\beta_{Sb} = \beta_{Cb}$	9.0357 (0.0109)	6.5806 (0.0372)	12.7790 (0.0017)

See the notes to Table V.

The results for the period since the first OPEC shock are broadly similar to the full sample results. As shown in Table VIII, the estimate of β_{S0} is greater than the estimate of β_{C0}, the estimate of β_{Cb} is much smaller than the estimate of β_{Sb}, and the estimate of β_{qb} is positive (except when b^C is used).

VI. Conclusion

The objective of this paper is to test which model provides a better description of U.S. stock market returns: a fads model or a bubbles model. Previous authors have shown that the fads model implies that apparent deviations from fundamental price will help to predict stock market returns. Our estimates of the relevant coefficient (β_b) generally support this implication. When we test the restrictions that the fads model imposes on the general switching-regression specification, however, we frequently reject these restrictions.

Table VIII. The bubbles model: 1973–1989

Coefficients	b_t^A	b_t^B	b_t^C
β_{S0}	0.0036 (0.913)	0.0014 (0.406)	0.0231 (2.095)
β_{Sb}	−0.0229 (−0.879)	−0.0245 (−1.051)	−0.0630 (−1.991)
β_{C0}	0.0025 (0.146)	−0.0636 (−1.337)	−0.0399 (1.145)
β_{Cb}	−0.1898 (−1.730)	−0.2431 (−1.765)	−0.1454 (−1.247)
β_{q0}	−1.1542 (−1.685)	−2.4383 (−3.148)	−0.3120 (−0.472)
β_{qb}	1.9339 (0.769)	6.2322 (2.092)	−1.3777 (−0.791)
σ_S	0.0368 (7.934)	0.0395 (13.825)	0.0345 (9.010)
σ_C	0.0749 (5.381)	0.0721 (5.553)	0.0758 (5.702)
Tests:			
$\beta_{S0} = \beta_{C0}$	0.0034 (0.9535)	1.8828 (0.1700)	0.1747 (0.6760)
$\beta_{Sb} = \beta_{Cb}$	2.1251 (0.1449)	2.5809 (0.1082)	0.3984 (0.5279)
$\beta_{S0} = \beta_{C0}$ and $\beta_{Sb} = \beta_{Cb}$	3.1280 (0.2093)	4.9634 (0.0836)	0.6708 (0.7151)

See the notes to Table V.

In our formulation, there are two key differences between the fads model and the bubbles model. The first arises from the fact that the bubbles model imposes a link between the bubbly asset and the alternative asset. This condition of the bubbles model implies that returns must be high in the states where the bubble survives to compensate the investor for the low returns in the states where the bubble collapses.

The point estimates of the parameters which reflect this difference tend to point in the direction of the bubbles model. The fads model implies that the slope and intercept coefficients should be the same in the two regimes. The point estimates suggest economically important differences between the intercept coefficients. If the slope coefficients were zero, the intercept coefficients typically imply that annualized returns in the surviving regime would be 40–70% higher than in the collapsing regime.

The point estimates of the slope coefficients (β_{Sb} and β_{Cb}) are also quite different. The bubbles model implies that the coefficient in the collapsing regime should be negative and smaller than the coefficient in the surviving regime. The point estimate of the coefficient in the collapsing regime is always negative and typically about four to five times smaller than the coefficient in the surviving regime.

The second difference between the fads and bubbles models arises because the bubbles model in section II suggests that a large bubble is more likely to collapse. In our formulation, this implies that the coefficient β_{qb} should be positive. Over the period 1928–89, this is what we find; moreover, the data strongly reject the hypothesis that $\beta_{qb} = 0$ for two of our three measures of fundamental price.

Although the rejections of the fads model point in the direction of the bubbles model, the evidence is not definitive. First, the statistical significance of the differences in the intercept and slope coefficients between regimes is weak. Over the period 1928–89, the marginal significance level of the test for equal intercept coefficients is generally around .10. In the test for equal slope coefficients, the marginal significance level is higher.

Second, intuition (and the derivations in section II) suggest that expected returns should be an increasing function of the size of the bubble in the states where the bubble survives. In our data, the relevant coefficient (β_{Sb}) has the opposite sign.

Taken together, our results suggest that there is more in the data than fads. The specific ways in which the data conflict with the fads model are frequently consistent with the bubbles model, but the evidence in favour of the bubbles model is not decisive.

We see a number of directions for further research. First, this paper examines stock market returns for the U.S. Thus, the usual caveat applies: our findings on fads and bubbles do not necessarily characterize stock market returns in other countries. It would be interesting to see if the patterns we find in U.S. data carry over to other countries. Second, our focus is on aggregate data. Future research might usefully examine returns for individual firms. Third, this paper studies stock market returns. It has been argued that fads and bubbles might affect other assets. Fourth, apparent anomalies in asset markets may arise because of strong assumptions about the constraints faced by agents. For example, Brock and LeBaron (1990) show that in a production economy asset pricing model, the introduction of finance constraints on firms can accentuate mean reversion.[21]

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[21] There is some empirical evidence to support this idea; see Jog and Schaller (1994). Woodford (1989) shows that imperfect financial intermediation can lead to non-linear (or even chaotic) dynamics. Gomes, Yaron, and Zhang (2001), in contrast, find that finance constraints are unsuccessful in improving the overall statistical ability of investment returns as a pricing factor.

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